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Strategic Planning for Universal Electricity Access

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Strategic Planning for Universal Electricity Access

by

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Abstract

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Fast growing and emerging economies face the dual challenge of sustainably expanding and improving their energy supply and reliability while at the same time reducing poverty. Critical to such transformation is the provision of affordable and sustainable electricity for the 1 billion people that do not have access and hundreds of millions connected to underperforming systems. However, expansion of electricity service in emerging economies is following the same century old paradigm under which power systems evolved: large central generation plants connected to load centers through a transmission grid and distribution lines with radial flows. This paradigm is now being challenged by the development and diffusion of modular generation and storage technologies. This dissertation contributes with models and results to help policy makers and private developers embrace these technological changes to develop cost-effective strategies to expand electricity access.

I use the SWITCH capacity expansion model to explore low carbon development pathways for the Kenyan electricity generation and transmission sectors under a set of plausible scenarios for fast growing economies that include uncertainty in load projections, capital costs, operational performance, and technology and environmental policies. This research investigates the generation and transmission costs and operational and environmental impacts on the Kenyan expansion pathway of these variables and policies. I find that the Kenyan power system presents a unique transition from one basal renewable resource – hydropower – to another based on geothermal and wind power for ~90% of total capacity. I also find that a cost-effective and viable suite of solutions includes availability of storage, diesel engines, and transmission expansion to provide flexibility to enable up to 50% of wind power penetration. Results suggest that fast growing and emerging economies could benefit by incentivizing anticipated strategic transmission expansion. "Zero carbon emission" by 2030 pathways are possible with only moderate levelized cost increases of between \$3 to \$7/MWh with a number of social and reliability benefits.

Traditional capacity expansion modeling that focuses on large-scale generation and transmission does not evaluate the potential contribution of distributed resources – modular technologies that can be deployed close to load centers. To improve on these modeling limitations, I use a novel

approach to assess the sequencing and pacing of centralized, distributed, and off-grid electrification strategies by developing and employing the Grid and Access Planning (GAP) model. GAP is a capacity expansion model to jointly assess operation and investment in utility-scale generation, transmission, distribution, and demand side resources. Contrary to the current practice, I find hybrid systems that pair grid connections with distributed energy resources (DER) are the preferred mode of electricity supply for greenfield expansion under conservative reductions in PV and energy storage prices. I also find that when distributed PV and storage are employed in power system expansion, there are savings of 15%-20% mostly in capital deferment and reduced diesel use. Results show that enhanced financing mechanisms for DER PV and storage could enable 50-60% of additional deployment and save 15 $/MWh in system costs. These results have important implications to reform current utility business models in developed power systems and to guide development of electrification strategies in underdeveloped grids.

A comprehensive development of electrification strategies requires complementing modeling results with empirical observations of the electrification process. I leverage two household budget surveys developed in Kenya in 2006 and 2016 as a unique data-driven window into the drivers of electricity access and the evolution of the electrification process. I find evidence that gains in electrification have come from grid extensions into rural areas as well as from people migrating from rural areas to cities, that rural grid extensions may be underutilized, and that poorer quintiles remain vastly unsupplied. Results highlight the role that modular technologies can play to complement traditional grid extensions to increase the pace and coverage of electrification efforts. Ultimately, comprehensive electrification strategies will need to integrate technological advances, new modeling paradigms, and the domestic socio-cultural context into policy making to advance electricity access decisively in low-income economies.

To Santi,

Sefora,

and everyone else’s future.

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I have spent now more than five years at the Electricity Markets and Policy Group at Lawrence Berkeley National Laboratory, which has become my second intellectual home. It was relatively clear to me that I was not going to use the research products from my work at the Lab for my dissertation. However, this dissertation is still deeply influenced by the researchers and friends from this community, their talent, and their advice. I am grateful to Alan Sanstad and Chuck Goldman for challenging me to become a more rigorous researcher and for teaching me so much about writing well and communicating complex concepts and results to policy makers. I am especially grateful to Pete Larsen, who over our years working together has transitioned from a supervisor to a friend and mentor. Pete has believed in and cared for me as a researcher and as a human being in every possible way, from supporting me through tough personal times to being very patient while I honed my writing and analytical skills and learned how to design and lead research. He has truly set up the highest bar for what being a supervisor means, and I hope I will live to these standards.

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Chapter 1

The challenge of electrification in low-income economies

1.1 Introduction

There are over 1.1 billion people in the world without access to electricity and over an additional billion connected to unreliable electricity systems (IEA and World Bank, 2015). A large majority of the increase in electricity access in recent years took place in urban areas; over 87% of the remaining deficit in access lies in rural areas (IEA and World Bank, 2015). This deficit is narrowing slowly but rapid population growth has made this deficit more or less stable in the last two decades (Alstone et al., 2015; IEA, 2014). This suggests the need to tap into innovative institutional and technical strategies to achieve the Millennium Development Goals of sustainable energy access for all by 2030 (AGECC, 2010).

Earlier understanding of fuel transitions in both high and low income economies was based on the concept of an "energy ladder" that households ascended with increased income and access to additional infrastructure (Barnes and Floor, 1996; Hosier and Dowd, 1987). Empirical evidence lead to several authors to reinterpret the transition process as a "stacking" or combination of energy sources, instead of a linear climb through a ladder (Heltberg, 2004; Masera et al., 2000). In more recent years, the focus has turned from energy sources and carriers towards energy services in an effort to understand the complex relationship between multidimensional sources and end-uses at the household level (Sovacool, 2011).

Understanding the dynamics of these micro-level transitions and the relationship between energy sources, carriers, and end uses is essential to develop adequate models for demand growth forecasting, particularly in rural areas (Wolfram et al., 2012). This knowledge is also important to comprehend the impacts of electrification through the energy services they provide in addition to the host of positive externalities associated with it (Casillas and Kammen, 2010). Both of these elements should be used to inform appropriate electrification strategies that increase life standards and drive productive activities.

Expansion of the regional or national central grid has been a prevalent strategy for increasing electricity access in high and low income countries. However, in low income nations electricity from the domestic power system is unreliable[1] – particularly in rural areas – so it is not immediately evident how much value it adds to new users when (and if) they are connected (Cader, 2015; Foster and Briceno-Garmendia, 2010; Foster and Steinbuks, 2008; Khandker et al., 2012). Very poor urban and rural inhabitants that are credit constrained may need time to save money to acquire

[1] For statistics in Africa, see (Eberhard et al., 2011, 2008; Foster and Briceno-Garmendia, 2010)

durable goods that translate into an increased demand for electricity (Gertler et al., 2016). Depending on tariff structures and connection costs, many poorer households may not even afford to connect to and/or consume from the electric distribution system even if they are close to it (Lee et al., 2015). An expensive central grid expansion could be overshooting these customers and be a suboptimal allocation of capital resources in these earlier stages.

Policy makers are confronted with a complex allocation problem: should they invest to extend a poorly functioning central grid, spend resources improving the quality of this grid, or allocate resources to decentralized resource development to improve electricity access to off and under the grid population? How should these decisions be designed, sequenced, and paced to achieve the best use of limited capital and other resources? How are these choices affected by the growth rate, level, and distribution of electricity demand along the intensive and extensive margins? How are these choices affected by the reliability and quality of the electricity delivery method? These central questions motivate this dissertation.

This dissertation creates a framework that can be used to assess rural electrification strategies and, more generally, expansion plans for national power systems in low-income economies, using Kenya as a case study. The framework is composed of a novel planning model that allows a joint assessment of distributed and utility-scale resources, and empirical research that tracks a decade of electrification efforts through two national surveys in Kenya. My goal is that this framework integrates these empirical results to help different stakeholders design electrification strategies based on sequencing investments in centralized and decentralized electricity supply. I also aim to inform policy making to create the right economic, financial, and social incentives to pursue these strategies.

1.2 System planning for sustainable and affordable electricity access.

The role that grid extensions and decentralized systems should play to provide electricity access has received increased attention in the past decade. This has been informed by decreasing costs of solar panels and other decentralized supply systems and by slow progress towards sustainable development goals. There is now a small but growing body of literature that describes models, results, and recommendations to improve electrification strategies. These studies use a variety of modeling approaches (e.g. general equilibrium models, constrained optimization, neural/fuzzy optimization, and cost-benefit analysis) and technological options to assess how to meet demand for different energy sources and/or end uses. I focus on the portions of this literature that analyze rural electrification specifically (for a more extensive review see (Kaundinya et al., 2009)).

Several studies use non-spatially explicit approaches to assess costs of expanding electricity access. Nerini et al. (2016) create a parametric model based on population density, LCOE of individual technologies, grid connection characteristics, and target levels for access. This methodology can inform initial assessments as well as provide inputs for spatially explicit models. Rosnes and Vennemo (2012) develop a regional estimate of electrification costs and needs for Africa that includes existing and "latent" demand forecasts, generation and transmission costs, and income elasticities. However, they do not analyze the role of decentralized resources in detail.

I am primarily interested in models that have an explicit spatial representation to analyze rural electrification, since this is relevant to study sparse areas in which distances between demand centers are high and demand is low. Zvoleff et al. (2009) analyze the spatial distribution of rural houses in four African villages using satellite imagery to identify how geography affects electrification costs. They find very dissimilar spatial distributions for these villages and assess how this affects costs through a simple network deployment model. Their network model is based on estimating the minimum spanning tree (MST) that connects all the structures identified using Prim's algorithm. Other researchers have refined the network deployment algorithm to study optimal transformer location and the size of the LV/MV grid to reach households by using heuristic models coupled with MST analysis (Kocaman et al., 2012). These analyzes are valuable for engineering decision making, but of limited policy applications due to their locational specificity. In this line, a large body of literature studies the optimal grid configuration for distribution systems (Navarro and Rudnick (2009) present a good review). However, their modeling approaches are too sophisticated for my research design, particularly because they deal with existing grids, many spatial restrictions in urban areas, and are limited to distribution systems only.

Intermediate level analyses have been performed at the national level by trading off spatial resolution and use villages, towns, wards, or similar small administrative divisions as the unit of analysis. An approach at the national level is developed by Mentis et al. (2015) in a case study of Nigeria. They apply a simplified heuristic algorithm that progressively electrifies "cells" either through a grid connection or a set of possible distributed resources with locational LCOEs. Several recent models implement a linear program (LP) or mixed integer linear program (MILP) in combination with a MST algorithm to study the cost trade-offs between expanding central grids and deploying DSS (usually diesel, solar, micro-hydro, or hybrid microgrids). Case studies and applications include Rwanda (Levin and Thomas, 2012), Kenya (Parshall et al., 2009), Ghana (Kemausuor et al., 2014), Zimbabwe (Nyakudya et al., 2013), and Ethiopia (Deichmann et al., 2011). Perhaps the closest study to my research proposal is that of Zeyringer et al. (2015) for Kenya. They develop a more thorough demand growth forecast that recognizes and estimates latent demand from homes that are not currently connected to the grid taking into account distributional concerns. They also develop a spatially explicit algorithm by splitting Kenya in cells and optimizing the costs of expanding the grid to interconnect cells plus the cost of supplying either local or "grid" electricity. They find that up to 17% of the demand could be met with PV microgrids. However, their analysis does not consider capacity expansion in central station generation, does not study in detail the pace of growth in demand or include any sequencing of investment, and does not include reliability representations for any of the sources.

Regional and continental level studies have explored scenarios for universal access with a simplified view of off-grid electrification options. Szabó et al., (2011) build a spatially explicit representation of solar and diesel costs, based on resource quality and transportation costs, respectively, for Africa. They estimate spatially differentiated LCOEs and compare them against an estimated grid supplied electricity cost to find that PV is as competitive as diesel, but that both are unaffordable to rural inhabitants in more remote parts of SSA. Bazilian et al., (2012) develop several scenarios for universal and sustainable energy access for Africa by 2030. They find that roughly the same investment in off and on grid systems is required to secure a minimum level of energy access. Compared to the national level models, they do not represent the network expansion decision explicitly and may over or undervalue grid extensions or off-grid strategies. However, they sequence investments and explore temporal patterns in more detail than these national studies, in addition to optimize over several generation portfolios while considering environmental restrictions.

This literature has neglected what I believe are very important variables in the decisions to expand central grids or develop microgrids and other DSS. This dissertation aims to fill several gaps that I have identified in the literature:

- Current analyses generally treat the decision of decentralized vs centralized electricity access as mutually exclusive, instead of understanding how these two sources can be used concurrently as an extension of the "fuel stacking" model (Masera et al., 2000).

- Current models assume the extended grid has perfect reliability or at least that is has the same reliability and product quality as a DSS. In many Sub-Saharan Africa nations the reliability of the existing power system does not allow connected users to use their appliances and derive value from the grid (IEA and World Bank, 2015). In turn, these models do not address reliability issues in decentralized systems, many of which are documented in the literature (e.g. Mink et al., 2010; Schnitzer et al., 2014)

- Most existing models usually neglect the expansion and environmental costs of the central grid generation and transmission. They focus largely on the distribution network expansion decisions and how they compare against DSS on a direct cost basis.

- Analysis to date have neglected transmission and distribution grid losses or if included use national averages that are heavily deflated by lower urban grid losses. Rural grid technical and non-technical losses are very high and commonly reach 25%-50% in low-income economies (Murthy and Raju, 2007). These studies also neglect distributed system losses and inefficiencies.

- Existing analyses largely ignore the dynamics of actual electrification and demand creation for poor and very poor customers. They produce and use very simplified projections that do not clearly reflect how important differences in income distribution affect connection and appliance purchase decisions, and general temporal, spatial, cultural, and social trends in actual connectivity.

- Current models generally do not consider the distributional and equity issues that arise from constrained investment decisions. These models typically estimate least cost expansions to achieve universal access without considering the important capital restrictions that affect most of these emerging economies. These results are very relevant to provide estimates of required investments, but are of limited use for domestic policy development and decision making.

- Some of the issues identified above reflect that many modeling efforts work on a "steady state" approach. While this approach is very useful to identify investment efforts and technology choices for universal access, they do not provide an assessment of the pacing and sequencing in these decisions and how they depend on the way demand grows.

Chapter 2 develops a comprehensive utility-scale planning model for Kenya, focused on sustainable and affordable expansion of the supply side. This project spends considerable effort in identifying the role that different variables such as demand growth, capital costs, and fossil fuel resources may have in power system development. These results inform the conceptualization and design of the core modeling effort in this dissertation, reported in Chapter 3. In this chapter, I develop the Grid Access and Planning (GAP) model, a unique electrification assessment tool that encompasses the supply and demand side of a national power system. There is no known tool that jointly simulates the investment and operation of the generation, transmission, distribution, and demand-side infrastructure in a power system.

1.3 Tracking the electrification process

The traditional approach to electrification is largely based on expanding the footprint of the existing electric utility to reach larger portions of the population. In some, but not all cases, this is accompanied by an expansion of the generation and transmission sectors to meet the expected new demand. The pressure of Sustainable Development Goal #7 – to provide affordable, sustainable, reliable, and universal electricity – has prompted most Low Energy Access (LEA) countries to pursue this traditional route. In this pursuit, there are two critical questions that need to be considered: how fast demand actually grows and how the actual electrification process has unfolded over time.

Determinants of electricity demand

Demand growth at the micro-level has generally been understudied in the literature. Macro level energy forecasts for emerging economies may be underestimating growth along the intensive and extensive margins for residential users (Wolfram et al., 2012). This is in part due to little understanding of the determinants of electricity demand in Sub-Saharan Africa (SSA) (Bhattacharyya and Timilsina, 2010). None of the existing analyses of rural electrification use appliance ownership to explain energy use, as they are based on indirect drivers such as schooling, income, or gender, among others. Most of these analyses do not track the temporal evolution of these determinants, nor do they consider income distribution among households. There is a gap in the development of appropriate bottom-up forecasting methodologies for the low-income and emerging SSA countries.

Several studies have employed microdata to understand the determinants of residential electricity and/or energy demand in emerging economies. Their methods and findings may be useful to frame my own work in residential demand forecast for Kenya. Louw et al. (2008) use 5-minute electricity consumption data from ~90 houses in two electrified South African villages to explain consumption using OLS. They find that electricity consumption is relatively inelastic to income, appliance ownership, and paraffin price, however positive in all cases. Negative elasticity was found on use of any firewood. Filippini and Pachauri (2004) and Pachauri (2004) reach a similar conclusion in demand being inelastic to income and price when examining a ~30,000 and ~100,000 household cross-sectional dataset from India, respectively. However, their income elasticity of ~0.62 roughly doubles the one found by Louw et al. (2008) of ~0.25. Both India studies found important significance of dwelling size and regional differences in explaining demand, probably expected from higher heterogeneity in their sample. None of these studies isolates the determinant for specific income brackets, which may be important if there are structural breaks. They also neglect to account for the impacts of reliability, which other studies have shown to reduce demand of electricity and its benefits (Khandker et al., 2012). Their cross-sectional nature does not allow investigating time variance of elasticities to produce more accurate forecasts, although seasonal difference in price elasticities were reported (Filippini and Pachauri, 2004).

Finally, the literature on national and regional energy-growth relationship is relevant to understand how assessments of household energy consumption using microdata can be harmonized with top-down approaches. Ozturk (2010) and Payne (2010) summarize the extensive research oriented to assert what the long and short-term causal connection between growth and energy/electricity (respectively) is. The literature generally tests four possible hypotheses: *neutrality,* for no relationship; *growth*, for energy causing growth; bidirectional if both are co-caused, and conservation for growth causing energy consumption (Payne, 2010). These studies test for "Granger causality", which essentially looks for statistically significant coefficients when performing OLS regression of a lagged time series X on a time series Y. The fact that lagged values in X can explain variation in present Y is interpreted as a "predictive causality" (Diebold, 2006). When time series are non-stationary, OLS estimates will be biased and different techniques are used including cointegration and auto-regressive distributed lag tests, among others. There is no agreement on the literature on which of the four hypotheses fails to be rejected most commonly, concluding that all four are equally plausible (Ozturk, 2010; Payne, 2010). However, my own analysis of the summary results from Payne (2010) suggests that low income economies disproportionally show income causing electricity growth, while in high income economies a neutral hypothesis is more common. Several African specific studies have examined causality and long-term relationship between energy and growth. Amusa et al. (2009) and Ziramba (2008) find that income is the most important determinant of aggregate and residential electricity demand in South Africa, respectively. Both find that price does not have a significant effect on demand. De Vita et al. (2006) find positive income elasticity of energy demand and negative of price and temperature in Namibia. Eggoh et al. (2011) find that the causal relationship between energy and growth in a panel of 21 African countries goes both ways. Kahsai et al. (2012) arrives to a similar conclusion for low-income Sub-Saharan African countries, but not for medium income SSA economies. Wolde-Rufael (2009) finds mixed causal results in different African countries, independent of their income status. These studies suggest that income and energy demand may be co-caused in some circumstances, which could play an important role in rural demand forecasting (Kirubi et al., 2009).

Empirical evidence on electrification processes

The abundant research on determinants of electricity consumption and relationship between consumption and growth is contrasted by a more limited account of how electrification processes are actually unfolding and the unique features of power system development in emerging economies. Historically, the first generation-distribution systems in emerging economies were typically deployed by an industrial facility to power its operations or by a few municipalities for street lighting. In SSA, colonial powers had little interest in expanding access to the local population, and in some cases even prevented it (Showers, 2011). By the mid-20th century, donor funding started flowing to finance larger electric infrastructure projects such as dams for hydropower, diesel thermal plants, and transmission lines. However, these were aimed to provide cheap electricity to industrial and mining operations and domestic users had low priority of access to the resource (Marwah, 2018). With some notable exceptions, such as Cote D'Ivoire and Nigeria, Sub-Saharan African countries became too indebted in the 1980s to attract private capital to expand their power systems.

These countries were only able to direct donor funding towards rural electrification programs by the late 1990s (Marwah, 2018). The delay in private involvement contributed to substantial state ownership of electric assets and subsequent inefficiencies (Shirley and Attia, 2017).

The history of electrification in SSA informs why most African countries still fail to provide affordable, reliable, and sustainable electricity to the vast majority of its population. Electrification was reserved for the few that could afford it, and the system grew unplanned and underfunded. Currently, seventy percent of utilities in SSA countries still rely on government-owned, vertically integrated utility structures with little competition, transparency, and monitoring (Attia and Shirley, 2017; RISE 2017). This arrangement leads to major operational and commercial inefficiencies: LEA countries score 2.9 out of 7 on reliability of supply in WEF's Global Competitive Index compared to 6.3 of OECD countries (Schwab, 2017). Transmission and distribution losses in LEA countries are on average 5-10 times higher than in AEM regions.

In addition to insufficient utility performance, LEA countries have traditionally low electricity consuming populations. The average per capita LEA country electricity consumption is 390 kWh/capita/yr, compared to 7,995 kWh/capita/yr in OECD countries (International Energy Agency, 2015). Low and stagnant consumption hinders cost recovery and worsens the financial health of current LEA utilities: their creditworthiness is 27% compared to 100% for utilities in OECD countries (Schwab, 2017). Revenues vary greatly by population and customer base, but almost all utilities in LEA countries operate under financial deficit (WB, 2017). All these factors – low demand, high system losses, and reduced transparency – hinder the capacity of LEA utilities to attract private capital to concurrently provide universal access, expand capacity, and reduce costs. This reality substantially conditions the development of electrification processes and hence the application of results from modeling efforts as the ones developed in this dissertation.

Several papers have critically assessed actual electrification processes in different regions, with a range of qualitative and quantitative methods. Taneja (2018) and Fobi et al. (2018) studied different aspects of the electrification process in Kenya. Taneja described the institutional and operational challenges that the Kenyan system is facing, making the case that building infrastructure is a necessary but not sufficient condition to increase electricity access to affordable and reliable electricity. Fobi et al. analyzed close to 140 thousand KPLC customers, tracked, and characterized their consumption growth over time. They found that consumption for recently connected customers is growing quicker and reaching lower levels than older customers did, and that urban customer's consumption is 50% higher than that of rural customers. For Southeast Asia, Palit and Bandyopadhyay (2016) problematize the predominant electrification strategy based on grid extensions, reviewing the shortcomings of its implementation in several regions. They propose a framework that integrates off-grid solutions with grid extensions as mutually complementary supply modes to increase access.

Chapter 4 develops a repeated cross-sectional quantitative analysis of the Kenyan electrification process between 2006 and 2016, using two unique microdata surveys that have not been analyzed jointly before. The empirical findings from this chapter complement the modeling work from Chapters 2 and 3, providing a robust understanding of the challenges and opportunities for electricity access in Kenya and, more generally, in emerging economies.

Chapter 2

Sustainable low-carbon expansion for the Kenyan power sector[2]

2.1 Introduction

There are over 1.1 billion people without access to electricity, a large majority of these in countries with very high levels of poverty (IEA and World Bank, 2015). Sub-Saharan Africa (SSA) is the most electrically disadvantaged region in the world with over 600 million people lacking access to electricity, and hundreds of millions more connected to an unreliable grid that does not meet their daily energy service needs (IEA and World Bank, 2015). There is an established relationship between electricity and/or energy consumption per capita and a host of well-being indicators such as the Human Development Index, infant mortality, and life expectancy (Goldemberg et al., 1985; Goldemberg, 1996). Mechanisms through which electricity access benefit the population are not clear, but there is a shared agreement that expansion in the capacity of consumers to use electricity will be key to lift populations out of poverty (Bazilian et al., 2010).

Developing sustainable power systems requires a set of institutional, regulatory, economic, financial, technological, and social conditions. One constraint in the implementation of these conditions is imposed by climate change and the need to stay below the 2 C threshold as agreed in the UNFCC Paris Agreement by mitigating and avoiding future greenhouse (GHG) emissions. Many fast growing and emerging economies have expressed concern that imposing restrictions on their future GHG emissions by forcing adoption of mitigation technologies would create a burden to their economic development (Dechezleprêtre et al., 2011). There are also concerns about the fairness of inter-temporal emission allocation between wealthier and poorer economies and metrics that should be employed to achieve such allocations (Baer et al., 2000; Page, 2008). Despite of these concerns, the stringency of climate change targets will require that economies in general cooperate to grow more sustainably as a whole (IPCC, 2014)

In this chapter, we explore sustainable growth paths for power systems in emerging economies through a case study of Kenya. The country is one of the fastest growing and most stables economies in Africa. To fuel this growth, the administration of President Mwai Kibaki launched in 2008

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The main content of the published paper has been placed in its entirety in the main body of the dissertation and the supporting information has been placed in its entirety in the Appendix of the dissertation.

the Vision 2030 initiative. The Vision 2030 is a long-term economic, social, and political development program whose objective is to make Kenya a middle income industrialized economy with high living standards for its population. One of the core components of this program is the Least Cost Power Development Plan (LCPDP), which lays out the investment needs for the electricity sector in Kenya. As of 2017, roughly 40% of the population has access to electricity, but only 15% of rural inhabitants do. Even in urban areas, power quality is low, supply is unreliable, and the system well-being is volatile due to its high dependence on hydropower (Ackermann et al., 2014). Emergency investments in diesel and fuel oil based capacity have rendered the country with one of the highest power costs in the region. However, Kenya is richly endowed with renewable and conventional resources that can be tapped to fulfill its development vision in an affordable and sustainable manner (Kiplagat et al., 2011).

Existing analyses of power system expansion at the pan-African level suggest capacity expansions between 50 to 200 GW by 2025 at around 8%-13% annual rates (Avila et al., 2017; Bazilian et al., 2012; Sanoh et al., 2014; Sparrow et al., 2002). However, there is little research in the literature for national level sustainable power system expansion for individual SSA economies. Some examples are found for Ghana (Asmah et al., 2015) and Nigeria (Aliyu et al., 2013; Avila et al., 2017; Gujba et al., 2011). Unfortunately, the methods used in these few studies lack the temporal and spatial resolution required to properly characterize variable resources such as wind and solar. These studies also use a very coarse representation of the power system, missing key elements such as transmission capacity and dispatch, geographical diversity, decrease in capital costs due to learning curves, and operational restrictions such as spinning and quickstart reserve margins. They also tend to focus on a narrow set of future scenarios, whereas in most of these growing economies there is important uncertainty on how their energy transition will be shaped. The system-level modeling and analytical approach employed in this chapter produce novel results not available in the current literature and that challenge current conceptions on technological choices in fast growing power systems. Specific features of emerging economies' systems like load uncertainty and growth rate, capacity constraints, and large endowment of renewable resources have not been studied integrally like we do in this case study for Kenya.

This chapter answers the following questions about cost effective expansion pathways for the Kenyan power sector:

- What are least-cost capacity expansion routes for Kenya to meet its future load?
- What is the generation and transmission costs and operational and environmental impacts on this expansion pathway of:
- Uncertainty in load projections and future load shape, including the adoption of energy efficiency and of residential air conditioning.
- Uncertainty in capital expenditures and operational performance of geothermal units.
- Uncertainty in coal generation unit capital costs.
- The adoption of battery storage technologies.

- Very high levels of renewable energy penetration.
- The adoption of environmental policies such as a carbon tax or a zero-emissions target.

In this chapter, we do not explicitly model the challenges of providing electricity to unconnected or underserved population – particularly through off-grid solutions – a topic we will address in the next chapter. The Kenya government has trusted the Rural Electrification Authority (REA) with the task of providing universal access to critical facilities and trade centers across Kenya. The Kenya Power and Lighting Company (KPLC) – the sole electricity distributor and retailer – reports increase in connections from 37% in 2014 to 47% in 2015[18].

However, it is still challenging to translate these progress results into load forecasts because not all inhabitants with access get connections and not all connected users can consume power due to affordability and reliability issues. We do not capture the latter because SWITCH-Kenya enforces perfect reliability at the generation-transmission level. We also use a coarse estimation for load projections, as there is much we do not know about the levels and spatial/temporal patterns of consumption and pace of growth that different customer classes will develop under different economic conditions. We do include an analysis of the effect of air conditioning adoption in the residential sector.

2.2 Methods and data

This analysis employs the SWITCH long-term planning model, which has been used to simulate a wide variation of power systems including North America, China, Chile, and Nicaragua(Carvallo et al., 2014; He et al., 2016; Mileva et al., 2013; Nelson et al., 2012; Ponce de Leon et al., 2015; Sanchez et al., 2015). SWITCH is a mixed integer linear program that estimates the least cost investment decisions to expand a power system subject to meeting load forecast and a host of operational constraints. The model concurrently optimizes installation and operation of generation units, transmission lines, storage, and the distribution system while meeting a realistic set of operational and policy constraints (see Table A.1 for values of operational constraints). SWITCH employs unprecedented spatial and temporal resolution for each region analyzed, allowing for an improved representation of variable resources like wind, solar, and storage. More information on the model can be found in the Supporting Information.

The SWITCH model implemented for Kenya is based on using the existing 47 counties as load zones or nodes (Figure 2.1). We assign existing generation units to each node based on their location and sum up individual existing transmission line capacity to reflect aggregate existing internodal (i.e. inter-county) transmission capacities. We extract existing generation capacity from the latest LCPDP report, totaling 1960 MW as of 2015 (approximately 25% geothermal, 35% hydro, 35% fuel oil, and 5% other resources) and transmission line data obtained from the Kenya Transmission Company (KETRACO) totaling 65 GW of transport capacity. Technologies considered for expansion include solar PV with one axis tracking, wind turbines, geothermal flash units, pulverized coal units, gas combustion turbines, gas combined cycle units, and diesel/fuel oil engines. We do include chemical battery storage as an expansion option in specific scenarios to understand its impacts on the power system and on the environment. We do not include new hydropower expansion in this study because we lack the high resolution temporal data required to appropriately model reservoir stocks and flows and run-of-river production. We also include neither technologies that are still in demonstration phase – carbon capture and sequestration or wave/tidal generation – nor technologies for which there are no proposed projects in Kenya, such as nuclear reactors and pumped hydropower. In addition, the model does not currently consider imports or exports with Ethiopia, Tanzania, and/or Uganda due to absence of appropriate data to model these exchanges.

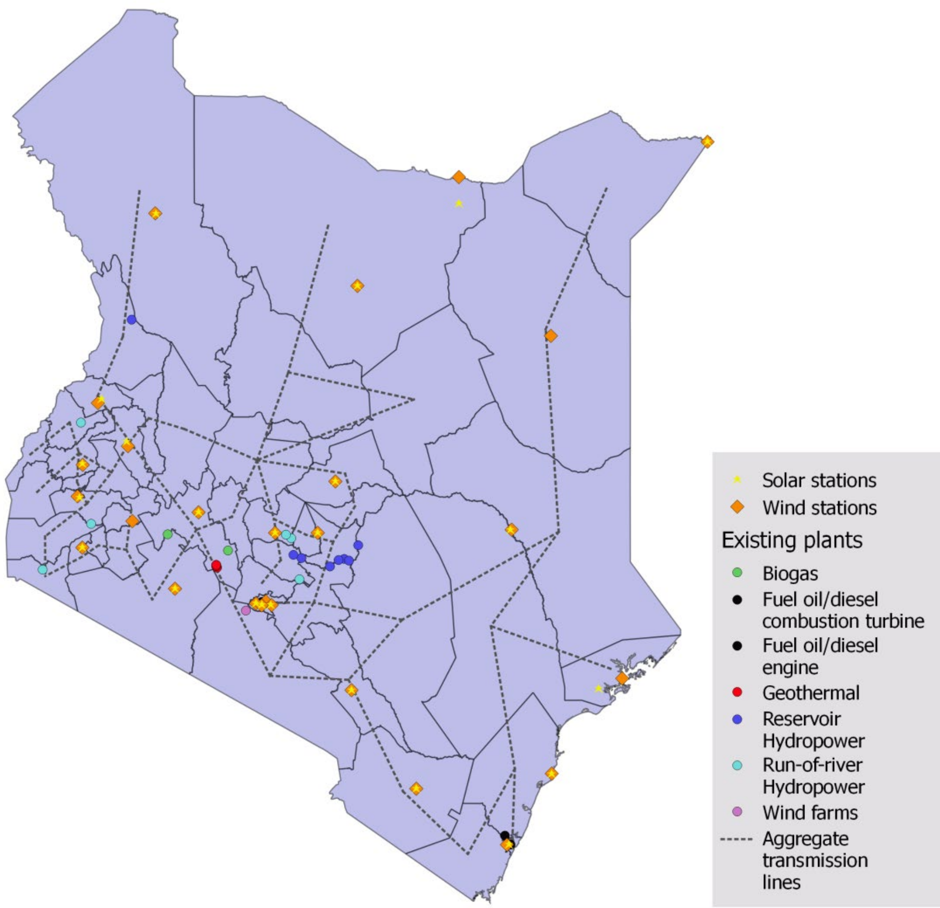


Figure 2.1 Modeled Kenya transmission system with location of existing and prospective projects and load zones represented by counties.

Temporally, the model base year is 2015 and runs from 2020 to 2035 in 5 year increments or "investment periods". This time frame matches the latest expansion master plan issued by the Ministry of Energy and Petroleum (Kenya MoEP, 2016). The model makes investment decisions for each of these four periods (2020, 2025, 2030, and 2035) and determines optimal dispatch for the operation of power plants in each hour of those periods. Each period is composed of 12 representative months that roughly reflect an average month on a given year. Each month is represented by its peak day (the day when peak monthly demand occurs) and a median demand day. Each day is simulated with its full 24 hours. The model then makes hourly generation, transmission, and storage dispatch decisions for 576 hours per investment period, or 2304 total hours. This sampling method captures adequately peak demand requirements, but may fail to fully account for all the energy required for a continuous period of months or years. This is particularly relevant for energy constrained power systems that rely on hydropower or that deploy large energy storage capacity. This is not the case for most of the scenarios we simulate, but still further testing in high temporal resolution production cost models is necessary to assure that energy consumption is met over extended periods.

We create load forecasts from annual peak demand and energy country-level sales forecast data by customer class extracted from Kenya Power and Light Company's (KPLC) 2013 Distribution Master Plan. While there are more recent load forecasts in LCPDP documents, the KPLC forecast is the only one specified by customer class. We estimate a daily hourly profile for each customer class that matches their expected load factor. We estimate average daily energy use from the annual consumption and modulate it by these daily hourly profiles to create hourly loads (see Figure A.1). This method omits intra-annual heterogeneity, but seasonality in Kenya demand is relatively low and we believe it adequately represents an expected load duration curve (see Figure A.2). To assign this country-level load geographically to SWITCH load zones, we use a specific method depending on the customer class. Residential and streetlight demand is distributed based on county population and urban/rural share as reported in the Kenya 2009 census. Industrial and commercial demand is allocated to each county based on their regional secondary and tertiary GDP as estimated by the World Bank (Sanghi et al., 2015). Hourly profiles are conservatively maintained through the projected forecast. However, we do estimate future air conditioning adoption at the residential level, its effect on hourly consumption, and its impact on capacity expansion decisions. Details of the method can be found in the Supporting Information.

Finally, "flagship" projects are specific industrial and technological initiatives supported by the Government of Kenya as part of their Vision 2030 program. We treat these as industrial loads for our forecasting purposes and allocate them by total county population, assuming that counties with larger population will have the human capital to host these projects. The KPLC forecast implicit growth rate is roughly 10% per year and starts from 2012. We compare the first few years of the forecast against actual energy and peak demand and find that actual growth is closer to 8%. We then adjust the base load forecast projection for all load zones to this level.

Fuel price forecast can have an important impact on the choice of future resources. We use the most recent World Bank commodity price forecasts for coal, oil (for diesel and fuel oil), and liquefied natural gas (LNG) (Baffes, 2016). On average, coal price is \$50/ton, oil is \$50/bbl and natural gas is 9-12 \$/MMBTu (see Figure A.3). For natural gas, we develop a supply curve that reflects the incremental investment costs in expanding the gasification terminal for LNG imports. These costs are estimated in 1.5 \$/MMBTu for each additional 3 MMm^3/day of maximum gasifying capacity. We use a diesel premium of 0.002 \$/MMBTu-km to reflect intra-country transportation costs to each different county, as calculated from the 2013 LCPDP. This version of the study does not include the use of biomass as a fuel to produce electricity, largely due to the absence of a proper market price for this fuel. Biomass share of generation capacity is currently about 1.5% (Power Africa, 2016).

Capital cost for non-conventional technologies such as PV and wind may decrease in the future. We extract PV cost forecasts from a 2015 study developed by the German Fraunhofer Institute (Mayer et al., 2015). Wind, combined cycle, gas turbine, combustion turbine, and coal unit costs come from a 2013 report by the U.S. Energy Information Administration (EIA, 2013). The costs for fossil-fuel based generation are fairly stable given the maturity of these technologies. For wind we assume a linear trend in capital cost reduction of 2% per year, in line with empirical results (Wiser and Bolinger, 2016). Geothermal unit costs depend importantly on their location. We use a list of prospective projects with their expected capital expenditure as reported in the 2013 LCPDP to assign a different cost to each geothermal project depending on its location. This essentially produces a supply curve for geothermal plants that recognizes the higher cost of prospecting, exploring, deploying, and operating geothermal units in certain locations (see Figure A.4). We derive costs for battery storage from the mid-scenario in Cole et al. (2016), with estimates at 0.7 \$/W and 488 \$/kWh in the current year decreasing to 0.5 \$/W and 192 \$/kWh by 2035 (Cole et al., 2016). Capital, variable non-fuel, and fixed costs for all technologies are shown in Table A.2. Costs are discounted with a 7% rate, which corresponds to the median historical central bank rate as reported by the Kenya Central Bank. We test 3% and 11% discount rates and find no changes in our results due to the short time span of the simulations.

Wind and solar PV technologies require hourly capacity factors for at least a year for SWITCH's dispatch module. We use NOAA meteorological data for 26 stations in Kenya that record global horizontal and direct normal radiation, wind speed and direction measured at 10 meters, dry bulb temperature, and atmospheric pressure (for location see Figure 2.1). We employ NREL's System Advisor Model to simulate the hourly production of a PV module with tilt equal to the latitude of the station. Wind turbine power curves are used to determine average production for each hour based on 15 years of hourly wind speed at an adjusted hub height of 100 meters and meteorological data. We finally translate production for both solar PV and wind turbines into capacity factors ranging from 0 to 1. We select 18 wind locations to site 600 MW projects and 23 solar locations to site 800 MW projects for a total technical potential of 10.8 GW of wind and 18.4 GW of solar PV, respectively.

2.3 Scenarios

Forward looking models like SWITCH-Kenya have little to no empirical evidence to be calibrated against. Therefore, their proper use is for within-model comparisons through scenario based analysis. The assumptions described in the preceding section produce a base case scenario or *business-as-usual (BAU)*. The outcome of this scenario should not be interpreted as the most likely pathway for future power system development, but as a benchmark given the assumptions that we are making about the different variables and their projections. The remaining scenarios are created to provide answers to the research questions presented in the introduction. A list of scenarios and brief description is shown in Table 2.1 and detailed key parameters are shown in Table A.4.

Geothermal energy: Geothermal energy is the largest energy source technically available in Kenya and may be the most relevant resource for domestic power system expansion (Kiplagat et al., 2011). The SWITCH-Kenya model includes over 8 GW of potential new geothermal capacity. While the technology is relatively mature, the risks involved in the exploration and operation of specific wells make final capital costs and capacity factors uncertain (ESMAP, 2012). We test the impact of higher than expected capital costs by shifting up in 30% the base supply curve. Separately, we test the impact of reduced and declining capacity factors due to lack of maintenance. The base capacity factor assumption for new geothermal is 94%, consistent with current flash steam technologies (Mines et al., 2015). The sensitivity is run with a base capacity factor of 85%

that declines 0.5% per year from the start of operation of a given project. We test two additional scenarios with half of the base case technical potential (4 GW instead of 8 GW). In one of these two scenarios, we also allow the deployment of storage.

Table 2.1 Scenarios used in the simulation

Scenario name	**Definition (expressed as variation from the BAU scenario)**
BAU	None
LowLF	Same energy consumption but lower load factor across all customer classes.
LowLoad	Reduced energy consumption, from implementation of energy efficiency policies across all customer classes.
HVAC	Alternative load forecast that includes adoption and use of air conditioning by urban residential customers.
HighGeoCost	Higher geothermal investment costs by 30%.
LowGeoCF	Lower and decreasing capacity factor from new geothermal plants.
RedGeo	Halve the technical potential of new geothermal.
RedGeoSto	Halve the technical potential of new geothermal, include storage as "Storage" scenario.
Storage	Allows up to 1 GW storage projects in each of the 8 largest load zones
LowCoal	Lower investment cost for coal generation, 70% of base cost.
CarbonTax-30	Apply a $30/tonCO2 carbon tax to fossil fuel based generation.
CarbonTax-10	$10/tonCO2 carbon tax to fossil fuel based generation.
ZeroCO2	Zero emissions from 2030, include storage as "Storage" scenario
ZeroCO2Sp	Zero emissions from 2030, include storage as “Storage” scenario and also constraint spilled energy to 5% maximum.

Load forecast: Load growth is the most impactful variable for power system planning (Carvallo et al., 2016). There is high uncertainty for load growth in fast growing and emerging economies that have large portions of their population without access to electricity and whose commercial and industrial activities are incipient and much more sensitive to economic performance. As mentioned, we already adjusted downwards the original load forecasts developed in the 2013 KPLC Master Distribution Study report. We then test three possible scenarios for deviations in load (see Figure A.5):

- First, we assess a case with similar energy consumption but lower load factors for all customer classes. The original load factors are 42% for urban and 36% for rural residential consumers and 83% for commercial/industrial and flagship projects. The resulting system level load factor is 64%. The sensitivity is run with 30% and 20% load factor for urban and rural residential load, respectively, and 66% for commercial/industrial, for a system load factor of 55%. This translates into ~10-15% higher peak demand for the sensitivity scenario compared to the base case scenario.

- Second, we assess the impact of more efficiency growth. The base case of 8% average annual load growth is tested against a more efficient annual growth of 5%.

- Lastly, we use a simple model of air conditioning adoption and use at the residential level to assess its impact on system expansion and operation (see Supporting Information for the methodology)

Coal power: Kenya is considering the use of domestic or imported coal to install and operate new generation units in Lamu and Kitui counties. There is strong resistance from environmental groups and local stakeholders to the adoption of this technology due to environmental and economic concerns. We run a sensitivity analysis on capital cost for coal plants to test how it affects adoption. The base capital cost for a single unit advanced pulverized coal plant is $3246/kW and the lower sensitivity cost is $2435/kW, 70% of the base cost. This value is the average of an alternative capital cost included in NREL's study of $2890/kW (Black and Veatch, 2012) and the expected cost for these coal projects as reported in the 2013 LCPDP of $2000/kW. We do not use this reported cost directly for several reasons. First, the reported cost at $2000/kW is much lower than any other international benchmark. Second, the country has no experience with coal plant deployment and the expected cost may be optimistically lower than the actual cost. Finally, the reported cost does not account for the additional infrastructure required to install the coal plant, which includes a railway, a port, and a dedicated transmission line to connect to the Kenya power system.

Storage: We run a scenario with battery storage units to be deployed in the main load centers. For this, we select the 20% of load zones with higher peak demand in the base load forecast scenario and allow the model to install up to 1 GW of storage on each site. We test whether the model chooses to deploy storage technologies and, if so, its capacity (GWh), discharge rate (GW), how it is operated, and what its economic impact is. Storage operation is simulated using a "circular" approach. This means that the charge at the end of the day matches the one at the beginning of the same day. This conservative approach does not require a pre-specified initial storage level, but does require further testing in more detailed models than SWITCH-Kenya to verify adequate system operation.

Climate policies: We finally test two sustainable growth scenarios based on climate policy constraints. In the first, we run the model twice with a $10/ton and a $30/ton of CO_2 carbon tax respectively, passed as a fuel adder based on carbon content for fossil fuels. In the second, we use a carbon cap to test the impact of a zero-emissions policy by 2030. The design of the tax policy is based on average social costs of carbon as found in the literature (Nordhaus, 2011; Tol, 2011). The carbon cap does not have empirical support, but we want to stress test the power system by forcing zero direct CO_2 emissions by 2030.

2.4 Results

The BAU expansion relies heavily in geothermal, natural gas, and wind technologies, which in total comprise over 70% of installed capacity and 90% of energy generation (Figure 2.2 and Figure 2.3). In this scenario geothermal reaches 3 GW of installed capacity by 2020 and 8 GW by 2035, using almost all the available technical potential. Wind power shows a steady progression from around 1 GW in 2020 to 6 GW in 2035. Diesel capacity remains relatively high and grows from 2 to 4 GW in the period analyzed. The base expansion is relatively low on emissions, totaling ~ 50 MT/CO_2 in the analysis period or ~2.5 MT/CO_2-yr. The average levelized cost of generation and transmission for the BAU scenario is ~ 82 $/MWh. Our BAU results are consistent with similar projection efforts developed in Kenya (see Supporting Information).

Scenarios that perform geothermal generation sensitivities are very relevant to gauge the future of the Kenyan power sector given its important role in the base case and overall abundant potential. Higher than anticipated geothermal costs would lead to delayed adoption of this technology, but would still reach the same 8 GW as in the base case by 2035. Wind power is the preferred least cost resource to replace the delayed geothermal capacity, with an expansion 20% higher than the base case (Figure 2.2). Higher geothermal investment costs translate to approximately 4 $/MWh additional average levelized cost, or a ~6% increment (Figure A.7).

The effect of degradation in the capacity factor for new geothermal plants is different from the impact of higher investment costs. The energy mix for this scenario is essentially the same as the scenario with higher costs (Figure A.10). However, the cumulative effect of reduced production requires the adoption of around 1 GW of coal capacity by 2035. Consequentially, this scenario has ~50% more CO_2 emissions (Figure 2.3). The cost impact is similar on average, but as production degradation is higher in older plants, these costs tend to rise towards the end of the analysis period.

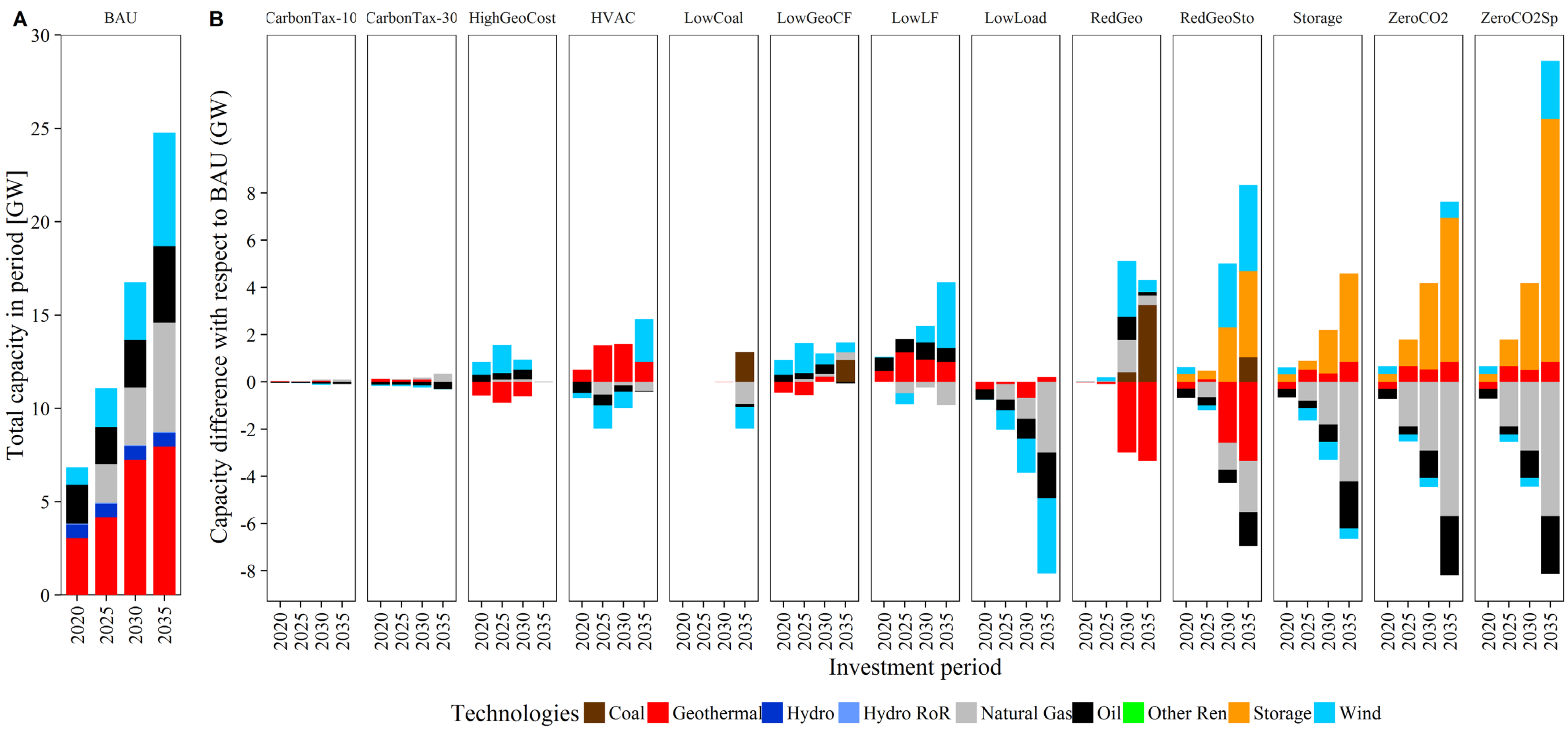


Figure 2.2 Cumulative generation capacity expansion for BAU scenario (A) and difference in cumulative generation capacity expansion for all scenarios when compared to BAU (B).

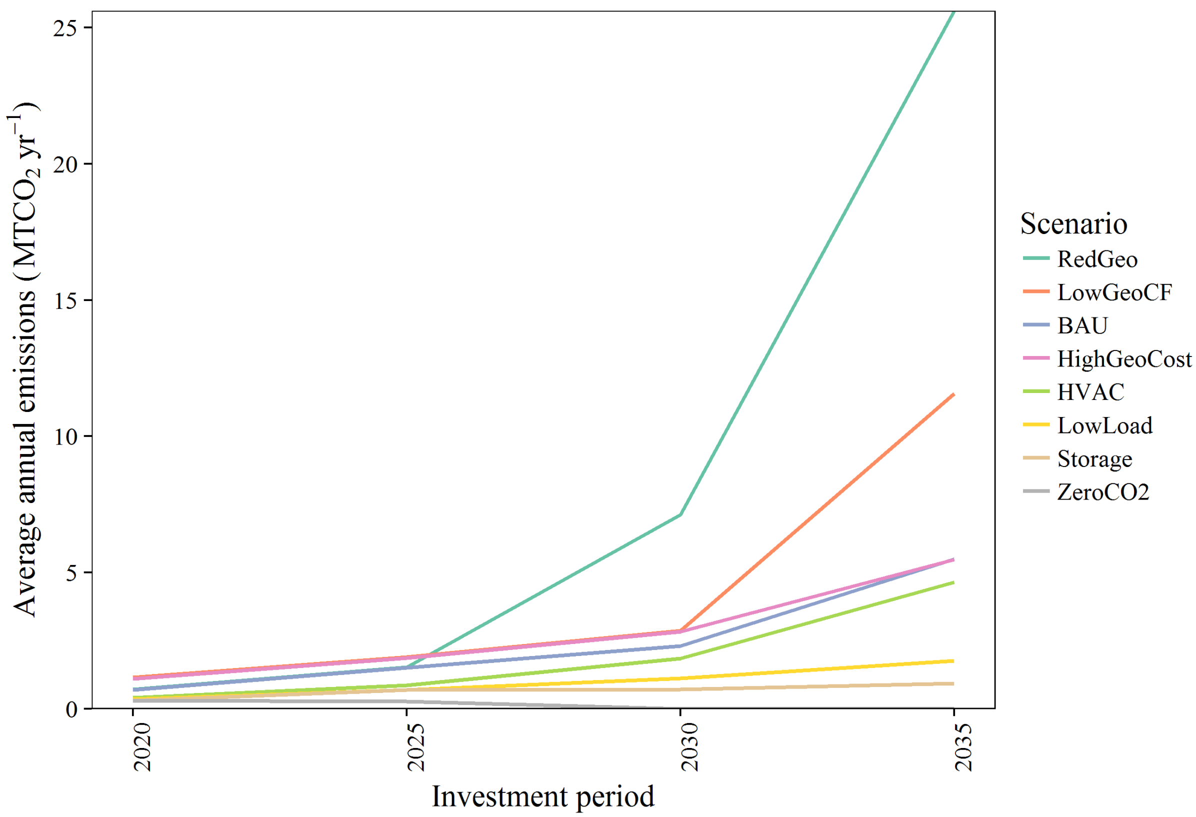


Figure 2.3 Average annual CO2 emissions for selected scenarios by investment period.

Our base assumption for portfolio availability is that there are ~8 GW of technically feasible capacity in Kenya. We test the impact of developing only half of this capacity or ~4 GW, which we implement by halving the maximum capacity of each of the 23 geothermal projects that the model can develop. We find little to no change in the capacity installed during the first two investment periods (Figure 2.2). However, once the available capacity is exhausted the expansion relies importantly in wind and natural gas in 2030 (about 4 GW) and coal in 2035 (about 3.5 GW). The levelized cost of these alternative pathways are on average 10 \$/MWh higher than the base case in the two latter periods (Figure A.7). Transmission costs are particularly relevant in 2030, as transmission capacity is required to enable the adoption of over 2.5 GW of wind in that period.

We simulate a variation of the above scenario by adding battery storage units to the portfolio of eligible projects, but still maintaining the restricted geothermal portfolio at half its base capacity. We want to test whether the availability of storage could delay or reduce the adoption of coal based generation. The hypothesis is that battery storage may enable higher cost-effective wind adoption by providing flexibility to the system. Indeed, the adoption of ~13 GWh of storage capacity at ~3.7 GW average discharge rate is correlated with a reduction of coal generation capacity to less than a third the original value and an increase of wind capacity of 80%. Diesel capacity additions are also reduced due to a systemic interaction between storage and diesel generation that will be discussed later.

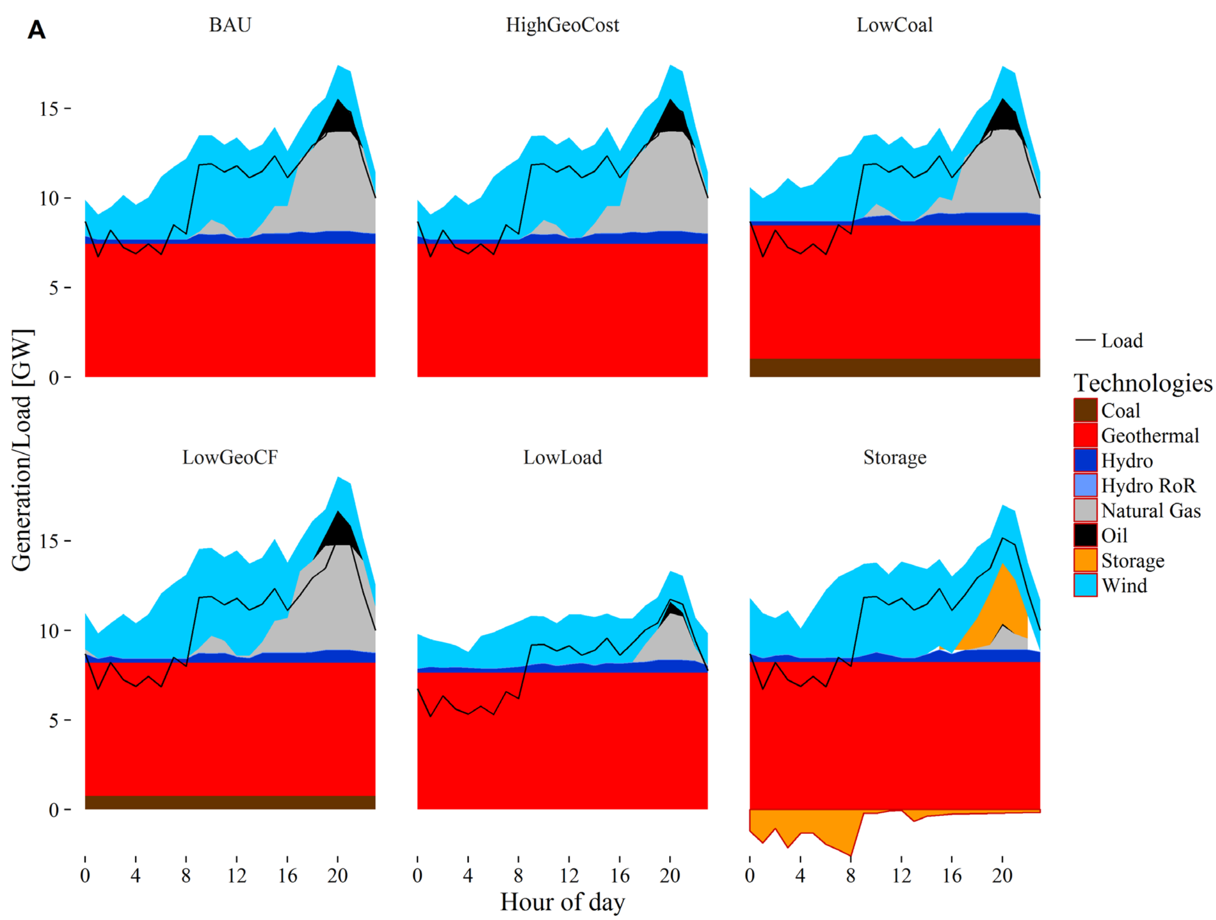
Load forecasting is very challenging for fast growing economies because there are many uncertainties on the types of energy services that the economy will demand, how they will be used in time, and who will have access to them. We test the impact of an "energy efficient" scenario in which electricity demand grows slower for all customer classes. The impact of 3 percentage points reduced growth (from 8% in the base case to 5%) is to install roughly 8 GW less of total capacity by 2035, as much as a third of the total capacity installed in the base case. Geothermal energy continues to be the least cost preferred resource and produces on average 75% of the generation during the analysis period. In contrast to the energy efficiency scenario, the impact of a lower than expected load factor is reflected in larger capacity expansion requirements for up to 4 GW or 20% of the base case. The expansion is in line with the 15% higher peak demand that lower load factor produces (Figure A.5). Our analysis of urban residential HVAC adoption reveals no significant impact on peak demand (Figure A.6). We estimate about 5% increase in midday demand by 2035 due to residential HVAC use compared to the BAU scenario. Interestingly, the improvement in system load factor due to the additional energy results in earlier geothermal power adoption, delayed wind capacity adoption, and reduced oil and natural gas capacity at the generation level.

The BAU scenario results do not include coal power expansion as a preferred least cost resource. Coal power has only been deployed so far in scenarios with rather extreme conditions, such as halving the technically available geothermal capacity or degrading geothermal performance. We test further the role of coal by testing a scenario with low capital costs for this technology. We find that a cost 30% lower than the base case has a modest impact on the adoption of 1 GW of coal generation by 2035 only. The largest systemic impact of adoption of coal is reduced need in transmission construction due to the displacement of more remote wind projects. In none of the scenarios analyzed in this chapter coal generation was adopted before 2030.

Battery storage has important cost reduction impacts due to the displacement of oil and natural gas generation and providing flexibility for the adoption of additional relatively inexpensive geothermal baseload. We estimate savings of around 15 $/MWh or 15% of average levelized system costs (Figure A.7). 13.5 GWh of storage capacity at 3.8 GW discharge rate are installed by 2035 – for an average of 3.5 hours of storage, about 15% of the total installed capacity of 22.6 GW for the "Storage" scenario (Figure 2.2). Geographically, this storage is initially installed close to the major load centers in Nairobi and Kiambu counties, but by 2035 there is storage capacity installed in all possible load zones.

We find that both levels of carbon tax at $10 and $30/ton$CO_2$ have a negligible effect in the resource expansion choices. An interesting outcome is that in both cases there are minimal reductions in wind power adoption compared to the BAU scenario. This is possibly due to the reductions in oil based generation triggered by the carbon tax and subsequently with the reduced flexibility in the system to absorb variable wind generation. In addition, we verify that these tax levels have no impact in emissions reductions compared to the BAU scenario (Figure 2.3). Results that are more interesting appear in the "zero emission" set of scenarios, in which we require the Kenyan power system to have zero emissions by 2030. The first implementation of this restriction – that did not allow storage – had no feasible solutions because without oil or natural gas generation the system did not have a large enough source of spinning reserve to operate reliably. To address this, we implement the "ZeroCO_2" scenario with the same storage options as in the "Storage" scenario. We find that the power system substitutes natural gas and oil based generation with storage, geothermal, and wind power to achieve zero emissions in 2030. 470 MWh of storage is installed in 2020, increasing to over 21 GWh by 2035 with a discharge capacity of 6.1 GW for 3.5 hours of average storage.

The "ZeroCO$_2$" scenario results in significant levels of spilled energy of 8% to 13% per year. Spills may be socially optimal under highly constrained conditions as the ones we are simulating. However, in many power systems with functioning markets, operators and project developers would not tolerate those levels of curtailment. We test a scenario in which curtailment is constrained at a 5% maximum – a reasonable threshold based on BAU curtailment – to assess its effects on the resulting expansion. The effect of this constraint is largely to promote earlier and more aggressive adoption of storage. This larger adoption of storage does not have a tangible effect in the choice of investments for other technologies, but does affect the system operation (Figure 2.4). The hourly dispatch shown in Figure 2.4 reflects how storage is charged in the night using baseload geothermal and available wind capacity, and then entirely discharged to meet the evening peak. The levelized costs of this alternative are 10%-15% higher than the scenario with socially optimal spills, in the range of 3 to 7 \$/MWh (Figure A.7). We also find an increase in the number of hours with zero short-term marginal costs in high renewable energy penetration scenarios compared to BAU (Figure A.11).



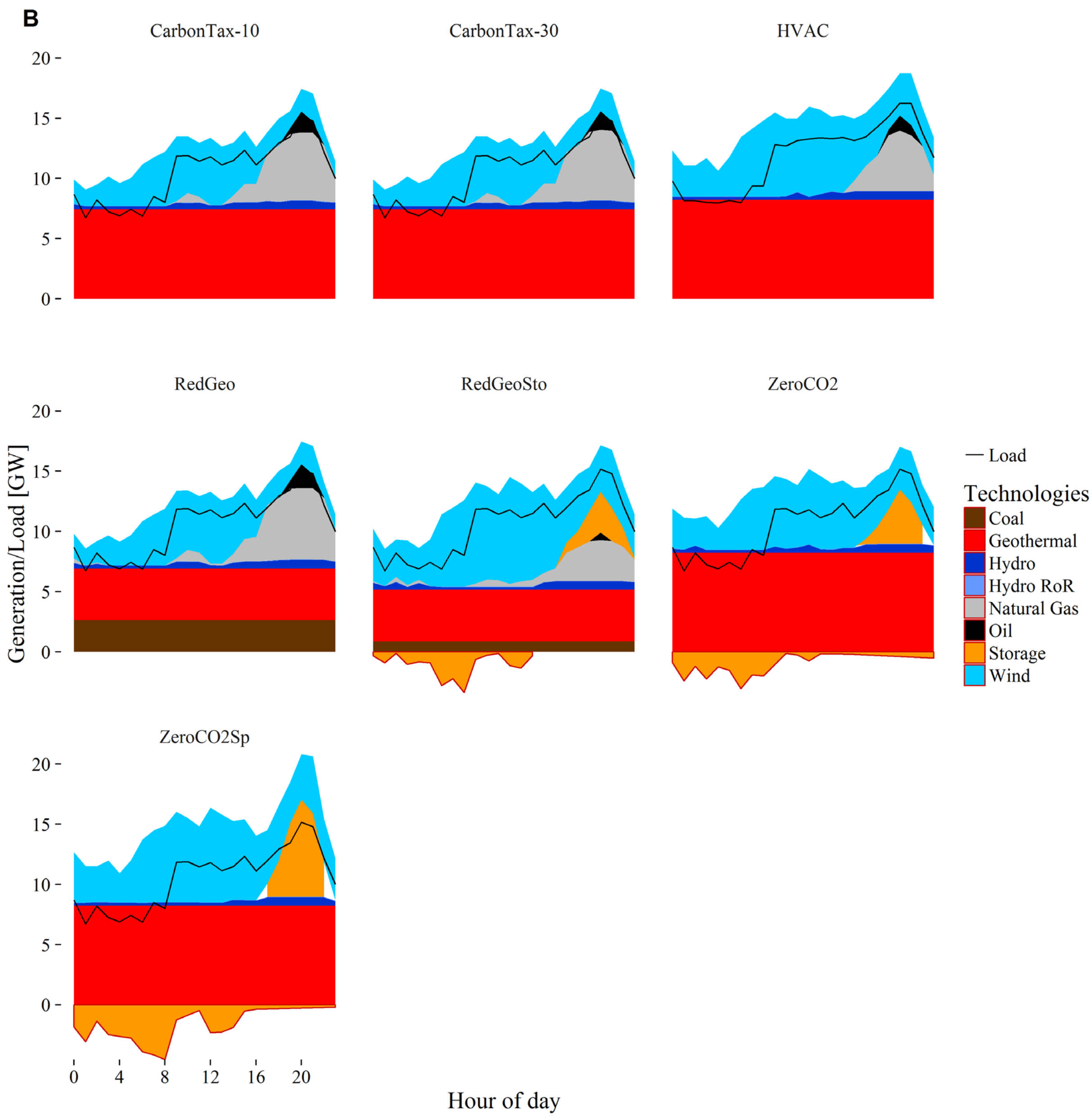


Figure 2.4 (A-B) Hourly dispatch for a representative day in May 2035 for all scenarios (panels A and B). Load is the same for all scenarios with the exception of the "LowLoad" and "HVAC" scenarios. The negative orange areas in some scenarios represent storage charging, which also appears as positive when it is discharging into the grid.

We measure the environmental impact of different selected scenarios through their CO_2 emissions. The BAU scenario for Kenya shows an eight-fold increase in emissions from 0.7 to 5.5 $MTCO_2$/yr (Figure 2.3), although the carbon intensity only increases from 20 $kgCO_2$/MWh to 50 $kgCO_2$/MWh (Table A.3). The increase in emissions in the power system is led by adoption of natural gas units. Scenarios in which geothermal power is not fully available are the most polluting due to coal generation adoption: lower geothermal capacity factor due to lack of maintenance can lead to double the BAU emissions by 2035 and a restricted geothermal portfolio to four times BAU emissions by 2035. In contrast, energy efficiency and storage adoption can lead to three to four times less emissions than BAU. In both these cases, the implicit carbon price is negative: these scenarios are more cost-effective and less polluting. The stringent "ZeroCO_2" scenario with restricted spills achieves zero emissions from 2030 at an average implicit cost of \$60 to \$140/tCO_2.

We put these results in perspective by estimating per capita emissions for the Kenya power system using population projections from the United Nations Department of Economic and Social Affairs (United Nations, 2015). Climate stabilization targets suggest average per capita emissions between 1 and 2 tCO_2/yr (Bolin and Kheshgi, 2001; Vergara et al., 2012). Based on data from the World Bank, we estimate that the electricity sector was responsible of 25% to 50% of total direct country level emissions in 2008. The lower range corresponds to low income economies and the upper range to OECD economies, although there is large variance within each income group. Then, a rough approximation for climate stabilizing per capita emissions from the electricity sector should be in the range of 0.25 to 1 tCO_2/yr. In almost all scenarios, the Kenya power system is well below this range, with BAU emissions per capita of 0.08 tCO_2/yr by 2035 (Table A.3). The restricted geothermal portfolio scenario produces the largest value of emissions per capita of 0.35 tCO_2/yr, still within the acceptable range. These results do not contemplate a potential massive electrification of end uses due to new technology diffusion and adoption, which may increase the pressure for low carbon system development.

2.5 Discussion

The Kenyan power system expansion reflects critical interactions between technologies and across input variables that apply to several fast growing and emerging economies in SSA and possibly elsewhere. In this discussion section, we highlight these interactions and how policy making could foster and enhance system level planning in Kenya to achieve sustainable growth. Our recommendations cover geothermal operation subsidies, integration of variable renewable resources, the role of storage and flexible generation such as diesel and natural gas, and the importance of forward looking transmission expansion.

A Kenya-specific result is related to geothermal plant investment cost levels and the importance of appropriate maintenance routines and standards. Higher investment cost does substitute geothermal, mostly for wind power. There are several phases in geothermal investment, starting with prospective exploration and test well drilling up to plant construction and operation. Higher cost for geothermal may then arise from unexpected exploration expenses as well as additional construction costs. Our results suggest that subsidies for geothermal investments may not be completely justified from a sustainability perspective, as the alternative pathway has equally low carbon intensity. However, subsidies and state involvement in the initial phases would probably still be relevant from a risk management perspective.

We show that even a small annual degradation in geothermal production performance has relevant long-term impacts in terms of resource choices. Performance of geothermal plants may have a larger effect than initial capital cost outlays, particularly from a sustainability perspective due to coal substitution in Kenya. Well casings and reservoir management are two critical sources of potential decrease in performance when not developed adequately. Higher standards for both processes and adoption of world-class practices may raise upfront costs. However, we show that these increases in cost have a lesser effect when compared to performance degradation in the long run.

A system level analysis is important to capture dynamics that otherwise are missed, particularly if they are not intuitive. We find that when geothermal potential is halved, over 75% of the gap can be filled with a non-baseload resource such as wind when storage is available. While the model employs battery storage and diesel peakers in other scenarios, it is very possible that the same flexibility services could be provided with new reservoir hydropower if it was available. Restrictions in dispatch on hydropower would probably require larger installed capacity to provide equivalent performance as dedicated battery storage. However, we find that the large amounts of variable resources can be integrated with relatively modest amounts of storage capacity. Then, even in the absence of battery storage, Kenya should be able to integrate large amounts of variable renewable resources using existing and potentially new reservoir hydropower in addition to the transmission expansion required to mobilize this power.

Storage can play a very important role in the future Kenyan power system by reducing the use of fossil fuels, particularly natural gas and diesel. This has an important impact on costs, with savings of 10 to 15 $/MWh, as storage enables the adoption of cost-effective resources that would otherwise would not be adopted due to operational restrictions in power systems. In scenarios with very tight emissions constraints, battery storage was indispensable for the system to operate within feasible regimes. The adoption of battery storage has also important distributional consequences: it enables the adoption of higher capital intensive non-dispatchable technologies such as wind and geothermal in lieu of dispatchable ones like diesel and natural gas generation. In these cases up to 90% of the system cost will be in capital, compared to 60% in the base case. This can have important implications for the trade balance of countries that import liquid fuels and also makes the power system and the economy more resilient to shocks and volatility in liquid fuel prices.

Flexibility is and will be an even more critical feature of future power systems with high penetration of variable resources and high load forecast uncertainty (Mills and Seel, 2015). We inspect the role that oil based capacity may have in future of fast growing and emerging economies power systems by comparing its installed capacity against that of wind (Figure A.9). When storage is not available, there is very high correlation between higher levels of wind capacity and higher levels of oil based generation capacity. The role of oil based generation as a key ancillary service and flexibility provider has been largely neglected both in the literature and electricity regulatory frameworks, with many countries making important efforts to decommission their existing oil based generation capacity as a sign of "progress." Our results suggest that market mechanisms should be designed to encourage diesel, fuel oil, and potentially natural gas generation capacity to be available to system operators to provide these services as well as meeting peak load. While availability of storage will reduce the need for oil based generation, in the short and medium term this will continue to be a key source for flexibility. These results are not advocating for *increase* in oil based electricity *production*. Oil based generation used for ancillary services and resource adequacy supplies only between 0.5% and 1% of total energy in any scenario. This translates to 40 to 80 hours of annual operation, roughly 500 times less than current diesel operation hours in Kenya.

We believe the proposed operational strategy for diesel based generation has low environmental impacts compared to system-level benefits. However, additional research using air quality and pollution dispersion models is required to assess the potential local and regional impacts of oil based generation. We design a set of additional scenarios in which we remove diesel generation from the portfolio to assess the economic impact of its moratorium in Kenya. This economic impact is an upper bound for willingness to pay for no diesel generation. We find that in the absence of storage, coal generation is adopted in 2035 to meet peak demand, with significant spilled energy, increased CO_2 emissions, and an additional system cost of 9-10 $/MWh. If storage is available, there is a 2-4 $/MWh increase in cost compared to a storage scenario that allows diesel generation. A no-diesel expansion path would be reasonable if Kenyan authorities determined that the marginal damage of diesel generation is above the 10 $/MWh level. More details of these simulations are available in the Supporting Information.

Another key provision of flexibility in power systems is transmission capacity expansion. Our results suggest that the Kenyan transmission system needs to grow 3 to 4 times in capacity by 2035 in all scenarios. However, the transmission expansion depends on the assumptions and conditions that affect the whole system (Figure A.8). A lower load factor than expected would require additional transmission capacity in excess of 40% to 50% of the base case expansion to meet the new higher peak load. In contrast, the energy efficiency scenario produces capacity savings in transmission expansion of over 25% compared to the BAU scenario. These large fluctuations in transmission capacity do not necessarily translate into significant costs, largely because of the low cost of expanding the transmission system in Kenya. We identify critical specific transmission corridors like the Nyeri-Kiringaya-Embu connector running through the center of the country to evacuate geothermal power to the load centers. Our results suggest that specific corridors should be prioritized through anticipated construction to allow the development of least cost generation. These interactions between transmission and generation should be a central component of least cost planning activities lead by the Kenyan Government.

The load uncertainty analysis reveals the potential effect of demand response (DR) and other policies that shape hourly profiles through automation and consumer behavior. Energy efficiency policies would save up to $30/MWh by 2035 or almost a third of the original average cost. This average cost of saved energy suggests there may exist plenty of cost-effective opportunities for the Kenyan system to use energy efficiency as an effective tool to meet load needs in the future. The "LowLF" scenario provides insights on the potential effects of DR. The shape of the hourly profile in the alternative load factor scenario is created by increasing the peak demand and decreasing the shoulder – middle of the day – and off peak demands. This has an interesting effect in the case of Kenya, where there is high wind availability in the shoulder hours. Higher demand in shoulder hours is met by existing wind capacity, saving about 15% of costs compared to the BAU scenario in the form of reduced natural gas generation that was originally dispatched in the late afternoon. This very specific result depends largely on our assumptions for the shape of the alternative low load factor hourly profile. However, it does suggest how displacing demand to match generation profiles for non-dispatchable resources that are already committed may create cost reductions. It also shows that DR programs may not necessarily be aimed to reduce peak demand, but also to match load profiles with generation profiles from non-dispatchable resources. The balance of these two dissimilar objectives is an open area of research.

An unexpected result is the absence of solar power investment on any of the resource expansion scenarios. This is unexpected because solar power has been a widely adopted off grid solution through solar home systems (Jacobson, 2007). In the case of Kenya, we believe the absence of utility scale solar may be justified by (i) the large potential of geothermal energy with lower levelized costs, (ii) the relatively better quality of the wind resource as a zero carbon source, and (iii) the low capacity value of solar photovoltaic in an economy with an evening peak throughout the year. These conditions are specific to Kenya and other SSA countries could still find solar PV cost-effective in the absence of other low carbon alternatives. Widespread adoption of air conditioning may shift the peak demand towards midday and enhance the capacity value of solar PV, making it a more cost-effective resource. Our results, however, suggest that by 2035 adoption will not be high enough to significantly increase the capacity value of solar PV.

Several shortcomings that stem from uncertainties and simplifications of the model and data could be addressed in future research to strengthen these conclusions. Among them, we find a need for better load forecasting tools, improved transmission representation to assess congestion conditions, intra-hourly assessments for variable resources – particularly wind power – and incorporation of demand response and other demand side resources. A deeper assessment of locational environmental impacts of each technology, particularly diesel and natural gas, is required.

Technological developments are expected to continue lowering the costs of low and zero carbon emission technologies. As our expansion modeling exercise shows, most of these technologies will be the basis for expansion in emerging economy's power systems. Critical environmental impacts will be related to the ability of these economies to cost-effectively and efficiently tap and integrate into these resources. Our results show that for Kenya delays or cost overruns in geothermal development lead to increases in both costs and carbon emissions due to adoption of coal generation. In contrast, adoption of storage and energy efficiency reduces emissions and costs through less use of natural gas and diesel. In a low carbon system, reaching the zero-carbon milestone by 2030 with technical feasibility will still be relatively expensive at \$60-\$140/tonCO_2. This suggests two strategies. First, the burden of mitigation should be borne by regions and jurisdictions with existing carbon intensive systems, possibly through environmental policies. Second, fast growing and emerging economies should focus on cost-effective development of their renewable resources, possibly through targeted technology subsidies, market design, and capacity building.

Chapter 3

Distributed resources shift paradigms on power system design, planning, and operation: an application of the GAP model[3]

3.1 Introduction

Power systems have evolved following a century old paradigm of planning and operating a grid based on large central generation plants and transmission lines (Hughes, 1993). It was not economic to build these units in small sizes and they had to be located far from load centers due to their environmental impact and resource availability constraints. This prompted the development of a hierarchical unidirectional network to move power to consumers, which led to the electric utility as we know it today. This paradigm is being challenged by the development and diffusion of modular generation and storage technologies. These systems are small and clean enough to be located very close to consumers and load centers, reducing the need for network infrastructure and suggesting that a reframing of the hierarchical paradigm is possible.

There has been extensive research on the effects of distributed generation on the operation of distribution systems (Barker and Mello, 2000; Borges and Falcao, 2003; Ochoa et al., 2006; Quezada et al., 2006; Walling et al., 2008) and of power systems in general (Azmy and Erlich, 2005; Begovic et al., 2001; Eftekharnejad et al., 2013; Slootweg and Kling, 2002). Voltage regulation, protection issues, and power recovery coordination are the main operational challenges identified. In recent years, many studies have documented the new challenges on planning distribution system expansion with high penetration of distributed resources (El-Khattam et al., 2005; Ganguly et al., 2013; Georgilakis and Hatziargyriou, 2015). A related stream of literature has documented the tensions that DER create between transmission and distribution planning (Basso, 2009; Gerard et al., 2018; Miller and Berry, 2018; Palmintier et al., 2016; Zhao et al., 2011). These studies suggest unpacking net demand into DER and load, redefining the boundary of both systems, and transitioning to comprehensive distribution-transmission planning processes and models. Despite these recommendations, there is no known research on how the whole power grid is designed, planned,

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The main content of the published paper has been placed in its entirety in the main body of the dissertation and the supporting information has been placed in its entirety in the Appendix of the dissertation.

expanded, and operated when modular resources are economically and technically competitive against large-scale centralized technologies.

This question is particularly relevant for power systems in regions with low electrification rates that could feasibly deploy these new technologies as an alternative to following the original grid extension paradigm. There is a growing literature that uses quantitative models to assess and recommend electrification strategies, their technological components, and costs (see e.g. (Deichmann et al., 2011; Kemausuor et al., 2014; Levin and Thomas, 2012; Mentis et al., 2015; Nerini et al., 2016; Nyakudya et al., 2013; Parshall et al., 2009; Rosnes and Vennemo, 2012; Zeyringer et al., 2015). However, these studies present several shortcomings:

- Treat the on and off-grid decision as mutually exclusive;
- Do not develop a temporal sequence of investments but a "snapshot" for the last year of analysis;
- Do not include generation and transmission expansion;
- Assume the existing power system is reliable, which is generally not the case in the regions where these models are applied.

The model developed for and used in this chapter addresses all these limitations by concurrently evaluating distributed and centralized investment decisions in production and transmission of power across time and space.

There are over 1.1 billion people without access to electricity, a large majority of these in countries with very high levels of poverty (IEA and World Bank, 2015). Sub-Saharan Africa (SSA) is the most electrically disadvantaged region in the world with over 600 million people lacking access to electricity, and hundreds of millions more connected to an unreliable grid that does not meet their daily energy service needs. There is an established relationship between electricity and energy consumption per capita and a host of well-being indicators such as the Human Development Index, infant mortality, and life expectancy (Arto et al., 2016; Goldemberg et al., 1985; Goldemberg, 1996). While the mechanisms through which electricity access benefit the population are not clear, there is a shared agreement that expansion in the capacity of consumers to use electricity will be key to lift populations out of poverty (Bazilian et al., 2010).

Expansion of the regional or national central grid has been a prevalent strategy for increasing electricity access in high and low income countries. However, in low income nations electricity from the domestic power system is unreliable[4] – particularly in rural areas – so it is not immediately evident how much value it adds to new users when (and if) they are connected (Cader, 2015; Foster and Briceno-Garmendia, 2010; Foster and Steinbuks, 2008; Khandker et al., 2012). Very poor urban and rural inhabitants that are credit constrained may need time to save money to acquire durable goods that translate into an increased demand for electricity (Gertler et al., 2016). Depending on tariff structures and connection costs, many poorer households may not even afford to connect to and/or consume from the electric distribution system even if they are close to it (Lee et al.,

[4] For statistics in Africa, see (Eberhard et al., 2011, 2008; Foster and Briceno-Garmendia, 2010)

2015). An expensive central grid expansion could be overshooting these customers and be a suboptimal allocation of capital resources in these earlier stages. It follows that a very relevant policy question is whether new modular and decentralized technologies can be a better solution and what the appropriate balance of centralized and decentralized resources is.

Contrary to the current practice, we find that:

- Hybrid systems that pair grid connections with decentralized PV, storage, and diesel generation are the preferred mode of electricity supply for greenfield expansion under conservative trajectories for future PV and storage prices.

- When distributed PV and storage are not employed in power system expansion, average LCOE increases by 15%-20% driven by increased diesel use and distribution grid expansion.
- Specific financing for DER PV and storage could enable 50% of additional deployment and save 15 $/MWh (~15%) in system costs.

These results have important implications to reform current utility business models in developed power systems and to guide development of electrification strategies in underdeveloped grids.

This chapter is structured as follows. We introduce the model in the next section. We then present scenarios and results from comparing a "traditional" system expansion against one with affordable and modular technologies that can be deployed at the distribution level (DER). This is followed by a sensitivity analysis on key parameters. We finally discuss these results and provide technical and policy recommendations.

3.2 Method

We develop a capacity expansion model with an explicit representation of transmission and distribution networks: the Grid and Access Planning (GAP) model. GAP has the ability to concurrently decide whether to expand the transmission and distribution systems and whether to deploy decentralized and/or utility-scale generation and storage resources to meet demand at prescribed levels of reliability. GAP is based on the SWITCH capacity expansion model developed at the Renewable and Appropriate Energy Laboratory at UC Berkeley (Carvallo et al., 2017, 2014; He et al., 2016; Mileva et al., 2013; Nelson et al., 2012; Ponce de Leon et al., 2015; Sanchez et al., 2015). The SWITCH model is described in detail in the Supplementary Information.

The GAP model should be used as a high-level planning tool by policy makers, and regulatory staff and utility planners who seek to understand the interactions between demand- and supply-side resources and their evolution over time. The model is not intended to produce investment decisions for network or resource procurement. The model creates internally consistent and reasonable least-cost expansion scenarios that can be ported into production cost and simulation models for a deeper level of analysis. This reduced technical accuracy is necessary for the computational tractability of the joint operation and investment of the whole power system.

Jurisdictions that allow vertical integration can particularly benefit from a joint generation-transmission-distribution model like GAP. This is the case of almost all of Sub-Saharan Africa, portions of Asia, and about half U.S. states (Shirley and Attia, 2017; Wilson and Biewald, 2013). However, even in regions were joint ownership of generation and distribution assets is limited, system operators can benefit from an integrative assessment to use rate design and incentives to guide adoption of distributed resources (Kahrl et al., 2016).

In this chapter, we develop and implement the GAP model to explore the conditions that affect adoption of centralized and decentralized resources in developed and undeveloped power systems. In particular, the distribution system – including node demand representation – is conceptual and represents a typical emerging economy medium voltage system. The implementation in this chapter borrows some basic parameters, topologies, and assumptions from the SWITCH-Kenya model to reflect conditions in emerging economies (Carvallo et al., 2017). We choose this approach to study broad questions on power system development with low cost distributed resources and produce generalizable results for power system planning and electrification strategies based on a choice of plausible assumptions and parameters. In this section, we introduce the model in generic terms; in the following section we discuss the Kenya-specific data sources we use to parameterize the model.

A. Model overview

GAP is implemented as a linear program whose objective function is to minimize the net present value of the capital costs from investing in generation and storage units; transmission lines; distribution grids; and DER, plus the operational costs to run and maintain these systems. The GAP model meets all or part of the demand at every node on every time step by installing and dispatching utility-scale and distributed resources, and the required transmission and distribution infrastructure. Generation operation constraints reflect different types, such as baseload, flexible baseload, peakers, and variable non-dispatchable. Transmission and distribution systems allow bidirectional flows, but there is no feedback allowed from the distribution to the transmission system. The model enforces spinning and non-spinning reserves that can be provided by utility-scale, distributed, and storage resources. The model can be configured to enforce constraints related to renewable energy targets, emission caps, reliability levels (% demand met), and level of end-use satisfied demand. Several "conservation" constraints assure basic power system physical performance is adequately represented. A mathematical representation of the model is available in the Appendix.

B. Spatial resolution

The GAP model represents an approximate primary distribution system by solving a network flow problem on a set of possible connections with supply and demand available on each node (see Figure 3.1). There is a single distribution system for each "load zone". Here we define a load zone as the spatial region served by a single node in the modeled transmission system. Each load zone is represented by a "head" node that is electrically equivalent to a stepping-down trunk substation (red dots in Figure 3.1). Existing and new potential utility scale generation is connected directly to this head node by dedicated transmission lines. The remaining nodes are "distribution" nodes, although we refer to them as "nodes" throughout this chapter (black dots in Figure 3.1). Distribution nodes are randomly positioned in space in this implementation, but with more detailed data they could represent existing villages, cities, distribution transformers, medium voltage (MV) segments, or other features and topologies at the distribution level. Nodes are connected by "distribution links" that are analogous to medium voltage circuit segments and possess length, losses, and capacity attributes. Distribution links can represent existing MV lines or prospective lines that do not exist but the model could choose to expand as part of the optimization.

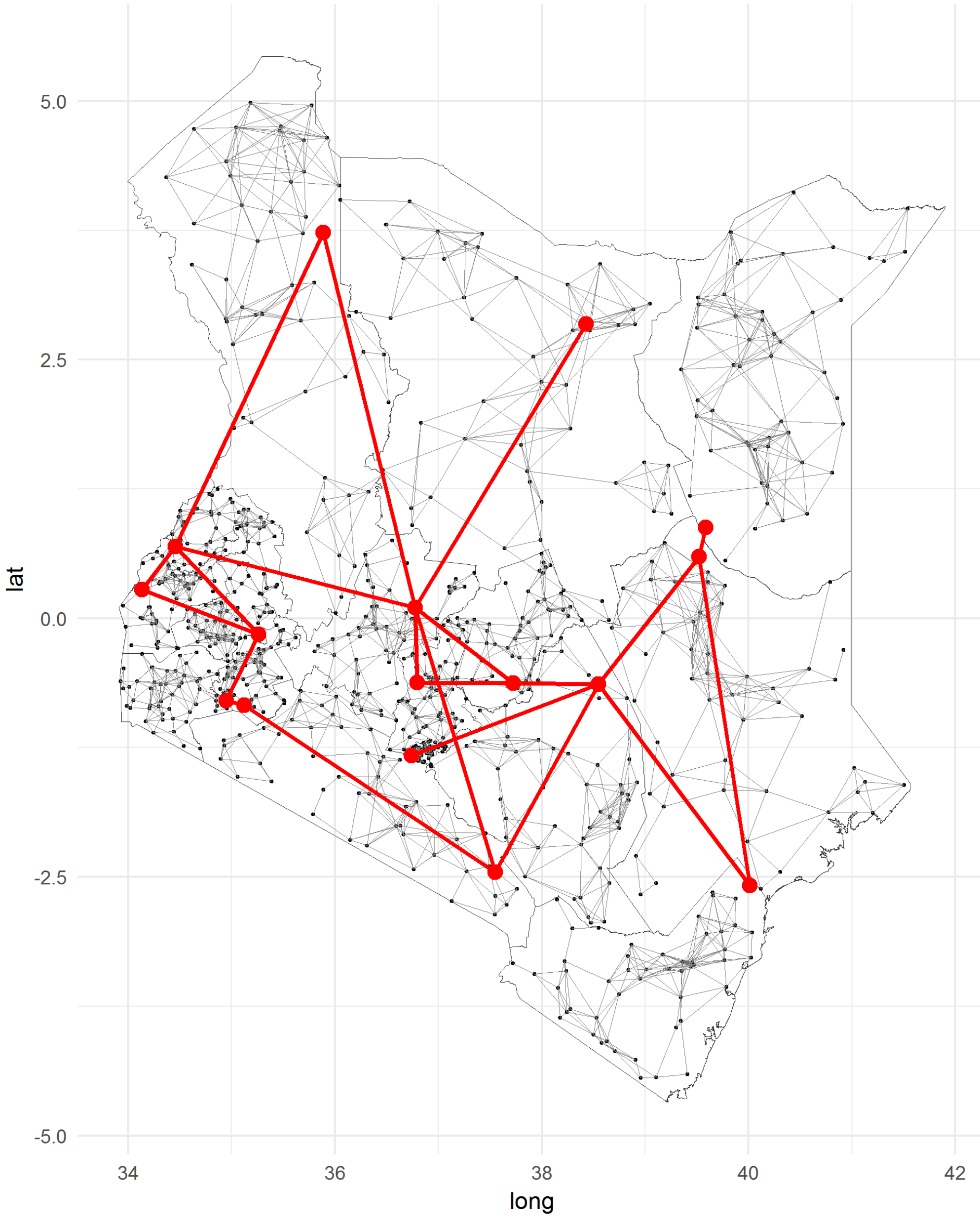

Figure 3.1 GAP model network implementation, including existing trunk transmission substations and lines (in red), distribution nodes (in black), and potential links between nodes (grey).

C. Temporal resolution

The model runs for three five-year investment periods: "2020" (2017-2022), "2025" (2023-2027), and "2030" (2028-2032). On each period, the model makes investment decisions to install utility scale or distributed generation, distributed storage, and to expand any of the transmission lines or install and expand any of the distribution links. Both utility scale and distributed storage are represented by a discharge capacity in MW and a storage capacity in MWh. The model represents days by sampling every three hours, for a total of 8 daily representative and chronological hours. Two days per month are selected for sampling – a peak day and a median day – that are weighted to reflect total energy demand for a given month. Four months are simulated per investment period, roughly representing all possible seasons in a given year. This way, the model simulates 3 [periods/simulation] x 4 [month/period] x 2 [day/month] x 8 [hours/day] = 192 [hours/simulation]. This sampling approach makes the modeling computationally tractable, which is not possible if all hours were used.

GAP jointly optimizes investment and dispatch costs by running a merit-order hourly dispatch to meet desired levels of demand in each of the 192 simulated hours. The model performs a joint dispatch of utility scale and decentralized generation/storage and transmission and distribution line flows, all subject to the available installed capacity on a given period. Storage dispatch decisions include charging and releasing of energy as well as a variable to track energy stored. The only distributed generation technologies that are not dispatched are the PV systems and the lighting-only solar home system (SHS). The latter is considered fully available at night hours from 7 pm to 1 am with zero marginal cost. The flows on transmission and distribution networks are the result of generation and storage dispatch decisions and are estimated using a transportation-flow model due to computational restrictions and non-linearity of power flow models with investment variables. While simplified, research has shown that transportation models' network investment decisions do not differ significantly from those based on DC optimal power flow models (Mai et al., 2015; Xu and Hobbs, 2019). Reactive power is not modeled directly, but sensitivity scenarios for distribution system costs and energy losses indirectly reflect the cost and operational impacts of reactive power management technologies deployed in actual distribution systems.

D. Demand

To simulate conditions prevalent in many constrained power systems present in emerging economies, the model includes a "decision to consume" variable that represents how much demand is satisfied on a given node and hour for a specific end-use and customer class (residential, commercial, or industrial). The model could potentially minimize costs by not serving any demand if this variable was left unconstrained[5]. The difference between the final value of this variable -realized demand - and the original or "latent" demand is the energy not served (ENS), a typical reliability metric (Billinton, 1988). The ENS is a metric that links system reliability with its worth (Billinton, 1994). The ENS could be included in the objective function if an appropriate value of lost load (VoLL) is available to quantify the cost of not serving demand. As there are no known VoLLs estimations for emerging economies, we do not include VoLL as part of the cost minimization in this implementation of the GAP model. The expected value of outages in generation, transmission, and distribution, is included by a de-rating factor on their available capacity. A stochastic representation of outages is outside the scope of the model.

[5] We actually verified that leaving this variable unconstrained in a cost minimization setup leads to no demand being met, an expected but important result for model consistency.

This “decision to consume” variable can be interpreted and used in different ways. First, it can be constrained to fulfilling certain end-uses for specific customers (i.e. meet all residential lighting demand). This setup can be used to study the cost and distributional effects of policy targets. Second, this variable can also be set to meet system-level reliability standards to understand expected temporal and spatial allocation of shortages. Finally, the node-level values for this variable reflect optimal allocation of consumption among types of customers and/or energy services.

Each node has a mix of residential, commercial, and industrial demand. The head node has a larger allocation of industrial demand representing higher voltage consumers that do not directly affect the remaining distribution system. Industrial and commercial demand profiles are characterized by a single representative daily consumption curve, respectively. Residential demand is split into different end-uses or energy services. End-uses are represented by specific daily consumption curves (e.g. lighting is only used in the evening and early morning). With this specification, we can study costs and timing involved in achieving end-use based electrification goals such as minimum lighting level provision, access to refrigeration, or access to entertainment, among others. We can also assess how different services are fulfilled under non-perfect reliability conditions. Representing demand through energy services also helps understand how customer preferences – reflected in the inputted demand profiles – affect system costs.

E. Technology options

At the utility scale, the model has natural gas combined cycle gas turbine (CCGT) and simple cycle combustion turbines (SCCT), diesel peakers, pulverized coal, run-of-river hydropower, and geothermal, solar PV, wind, and battery storage technologies available for installation. At the distributed scale the available technologies are diesel generators, solar PV, battery storage, and solar home systems (SHS). For distributed solar PV we use the same radiation data employed in the utility scale plants to estimate an average radiation at the load zone level, although the model supports node-level values if needed and available. Finally, SHS is configured to meet lighting and charging demand only; it cannot be used to meet demand from other end-use services. This is to supply the most basic access level (Tier 1) as defined in the World Bank’s Multi-Tier Framework (Bhatia and Angelou, 2015).

3.3 Setup and parameterization

The version of the model implemented in this chapter uses 16 load zones connected between themselves by 23 transmission lines whose location and capacity are based on an aggregation of the existing Kenyan transmission system. Figure 3.1 shows the portfolio of distribution system nodes and links in all load zones. In this greenfield study, we initialize the model without distribution lines; candidate inter-nodal connections or “links” are generated with a random graph algorithm. The density of the random graph can be chosen arbitrarily, but our calibration determined that an average of 5 candidate links per distribution node was an adequate balance of computational capacity and system representation (see details of the random graph creation in the Supplementary Information). With this density of candidate links, both radial and fully meshed solutions to the optimization algorithm are possible. We initialize each zone with 50 nodes and between 140 and 190 bidirectional links per load zone, for a total of 800 nodes and ~2900 possible MV segments in the model. For reporting purposes, load zones are classified in three categories according to their density: high, medium, and low (also referred as sparse). Density is based on load zone surface area and population for Kenya according to the 2009 census. Load zone surface area differences translate into different inter-nodal distances. Mean distance between nodes is 12, 28, and 44 km for high, medium, and sparse density areas, respectively. There are over 79,000 km of possible links that the model can choose to expand[6]. The distribution system in this simulation will be the result of investment choices in expanding any of the available 2900 links and/or installing decentralized resources.

Numerical parameters at the generation level include fuel and capital cost projections for each technology, variable non-fuel and fixed costs, and hourly capacity factors for each wind and solar site. At the transmission level the main parameter is the extension cost, set at 1,000 $/MW-km based on Carvallo et al. (2017). A complete list of numerical parameters at the generation and transmission level is provided in the Supplementary Information.

At the distribution level, relevant numerical parameters include distribution system losses, grid extension costs, capital cost of distributed resources, and diesel fuel costs. Though losses are a nonlinear function of power flow, to preserve the linear structure of the mathematical program we model losses as linear inefficiencies that are proportional to distance and delivered energy. We employ a benchmark of 15% losses per 100 miles of distribution line applied to the segment distance. Base distribution grid extension costs are set at 35,000 $/MW-km, which we derived from actual project development documents obtained from the Kenya Rural Electrification Authority. This value varies substantially across case studies and analyses in other countries. Other electrification studies have used values in the $2,000-$8,000 per MW-km range (Parshall et al., 2009; Zeyringer et al., 2015). Therefore, we test a range of expansion cost values from 2,000 to 35,000 $/MW-km as sensitivities. Costs for distributed storage, PV, and diesel generators are set at 1.5, 2.5, and 1.5 times the corresponding value for their utility scale equivalent, respectively. This relationship guarantees consistency between potential utility and distributed scale technology cost variations. Diesel fuel costs vary by load zone, but without more detailed local pricing information we assume the distributed level fuel costs are the same as the utility scale for a given zone. Diesel generators have the same capital cost in $/kW in any place, but fuel costs vary by load zone according to the premium paid for transportation estimated in the 2015 LCPDP. Capital costs for all technologies and fuel costs come from the SWITCH-Kenya model (Carvallo et al., 2017). See Table B.1 in the Appendix B for values used in this simulation.

For this chapter, we implement a simplified model to create hourly demand forecasts and to allocate loads to nodes. Residential sector demand is split in five end-uses: lighting, television, refrigeration, ironing, and other large appliances (washer, dryer, or air conditioning). Each appliance or end-use is represented by a 24-hour demand profile sampled every 3 hours to match model daily resolution. Homes are segmented in three socio-economic levels and each level is endowed with a portfolio of appliances and a level of consumption, based on data from the 2005/2006 Kenya Household Budget Survey (KHBS). Each node has a specific initial share of households on a given socio-economic level, ranging from 0-5% for high consumers, 10%-30% for medium consumers, and the remainder for lower level consumers. We represent the intensive margin as consumers moving into the next consumption or socio-economic level based on income increases derived

[6] As a point of comparison, the Uganda medium voltage system had an aggregate length of 16590 km as of 2017.

from GDP growth forecasts from the World Bank. The extensive margin is represented by population growth per node. This means that the share of consumers by node changes on each investment period. We calibrate and verify the consistency of the residential demand forecast by calculating annual energy consumption, peak demand, and load factors and compare them with values reported by the domestic Kenya utility KPLC. Commercial and industrial forecasts are based on allocating into nodes existing projections used by Carvallo et al. (2017) and derived from domestic Kenya sources. Commercial demand is allocated in proportion to the population represented by each node. Half of industrial demand is allocated to the head node and the other half allocated randomly to the remaining nodes. We use a 24-hour demand profile to represent temporal consumption patterns for each segment. For simplicity, the demand profile for industrial and commercial customers does not change with seasons or investment periods. We calculate that commercial and industrial load factor is 55% and 73%, respectively, which is in line with typical values for this metric.

The GAP model is implemented in AMPL and solved with CPLEX 12.0 on a server with four Intel™ Xeon™ processors running at 3.33 GHz and 32 GB of RAM. Depending on the setup, the model solves approximately between 10M and 13M variables using a barrier algorithm with no crossover. The crossover simplex/dual iterations were computationally intensive, possibly due to numerical instability, and took between 80% and 90% of the solution time. To address this, we performed several test runs using simplified versions of the model to compare solutions with and without crossover. No-crossover solutions were acceptable for our purposes in terms of possible infeasibilities and suboptimality. Simulations used for this chapter took between 90 and 120 minutes each to solve.

3.4 Scenarios

As with any forward-looking model, GAP has little to no information to use for calibrating its output. The best use of these types of models is for scenario analysis. This analysis is focused on assessing the types of power systems and overall expansion strategies that are optimal under a scenario with affordable modular generation and storage that can be located close to load centers. We then create a "traditional" expansion scenario in which grid extension and diesel generators are the only resources that can be used to supply distribution loads. We use this scenario as a benchmark to assess different electrification routes that employ other technologies and that are subject to different constraints. These sets of scenarios are summarized in Table 3.1.

The "BAU w/o DER" and "BAU w/DER" cost minimization scenarios are compared and used to evaluate the impact of a full suite of technological options for distribution system expansion. The "BAU w/o DER" scenario replicates the "traditional" expansion paradigm using central grid extensions and distributed diesel generation only. However, neither of these scenarios represents existing distribution, transmission and generation infrastructure. Therefore, we develop an additional scenario, "BAU w/o DER Sys" in which we include existing generation and transmission infrastructure available from the SWITCH-Kenya model to test its impact on system expansion results.

The next five scenarios are sensitivities on key parameters. The "GridExt" cost minimization scenario is used to analyze sensitivity to distribution grid extension costs. The "Losses" scenario studies the effect different distribution system losses parameters. During our exploratory analysis, we identified these two variables as the most impactful and with the highest policy implications. We then explore two key technology sensitivities. "LowBatLife" assesses the impact of reduced battery storage lifetime due to potential frequent cycling and regulation. "LowDGCost" explores the effect of the most optimistic capital cost reductions for distributed PV and storage. Finally, in "LowOff" and "HighOff" scenarios the financing rate for distributed PV and storage is set at 1% and 15% real annual, respectively. Financing rates could be substantially affected by effective policy intervention to pool customers and improve creditworthiness. We then test the impact of public financing at social rates versus more expensive private financing on system expansion decisions and costs.

Table 3.1 Summary of GAP scenarios

Scenario code	**Distributed PV-Storage allowed?**	**Description**
BAU w/o DER	No	BAU scenario with no pre-existing transmission and generation, which allows only grid extensions and distributed diesel generation to supply distribution nodes
BAU w/o DER GridExt	No	Identical to above with grid extension costs sensitivity at $2000, $10,000 and $20,000 per km-MW. Default is $35,000 per km-MW
BAU w/DER	Yes	Identical to BAU w/o DER, but allows distributed PV and storage.
BAU w/o DER Sys	No	BAU without DER, including the existing transmission and generation system in Kenya.
GridExt	Yes	BAU w/DER with grid extension costs sensitivity at $2000, $10,000 and $20,000 per km-MW. Default is $35,000 per km-MW
Losses	Yes	BAU w/DER with losses parameter sensitivity at 3%, 5%, 10% and 15% per 100 mile of distribution line. Default is 15%.
LowBatLife	Yes	BAU w/DER with battery storage life reduced to 5 years. Default is 15 years.
LowDGCost	Yes	BAU w/DER with and lower capital costs for PV and storage. PV now reaches 1013 $/kW by 2030 and storage reaches 90 $/kWh by 2030. Default is 1900 $/kW and 309 $/kWh by 2030, respectively.
LowOff	Yes	BAU w/DER with 1% annual real financing rate for distributed PV, storage, and SHS. Default is 7%.
HighOff	Yes	BAU w/DER with 15% annual real financing rate for distributed PV, storage, and SHS. Default is 7%.

3.5 Results

The results section is split in two subsections. In the first subsection, we use the GAP model to understand the impact of investment decisions, costs, and system efficiency of DER adoption on power system expansion by:

- Comparing system expansion with and without the existing generation and transmission infrastructure.
- Examining and explaining supply investment choices.
- Studying the impact of DER in system efficiency and capital deferment

- Assessing the cost impacts of DER availability and adoption.

In the second subsection, we assess the robustness of the results from the first subsection through sensitivity analyses of key parameters. Generally, results are reported for the three node density categories – high, medium, and sparse – and in some cases for the three investment periods – 2020, 2025, and 2030.

A. Existing transmission and generation infrastructure have little to no influence on system expansion by 2030

We first simulate the expansion for a power system with no pre-existing infrastructure and limited technology alternatives. Only diesel generation and distribution system extensions can be used to supply retail consumers, in addition to expanding transmission and utility-scale generation. This scenario replicates the century-old paradigm for least-cost power system expansion based on grid extension and diesel generation for off grid areas. In addition, we run an identical scenario that includes pre-existing generation and transmission infrastructure installed in Kenya as of 2015. We compare results for both of these scenarios to find the resource allocation decisions are almost identical.

B. Availability of distributed PV and storage dramatically changes supply choice and system evolution

We study the "traditional" expansion with no pre-existing system and find that between 75% and 80% of supplied energy comes from utility-scale resources, while 20% comes from distributed diesel generators. However, about two thirds of the nodes have diesel generators installed and half of those nodes are connected to the distribution system in "hybrid systems" (Figure 3.2, left panel). Even in dense load zones, over half of the nodes have diesel generators installed even if these nodes are connected to the distribution system. Hybrid systems are the most common arrangement in load zones with medium density, while in sparse areas over 75% of nodes have diesel generators in off-grid mode and 20% are supplied with a grid-diesel hybrid mode. The prevalence of diesel generation in the "traditional" expansion is consistent with underbuilt and unreliable power systems, as is the case of Nigeria, especially if all demand must be met (Punch, 2017). In addition, high connection costs make any distributed generation resource more cost-effective. Distributed diesel generation capacity in a scenario with low expansion costs is two thirds of that in the BAU case and its production is four times less (see Figure B.17).

The role of diesel to meet peak demand explains the difference between diesel deployment and production (Figure B.1). In dense zones where diesel generation is installed, it is exclusively used to meet peak demand in the evening hours. In medium density areas in peak hours, about half of demand is met with diesel generation. However, in off-peak hours less than 10% of demand is met with this resource. In sparse areas, only the nodes closest to the trunk substation are grid connected. Consequently, on average about 80%-90% of peak demand is served by diesel generation in an off-grid mode.

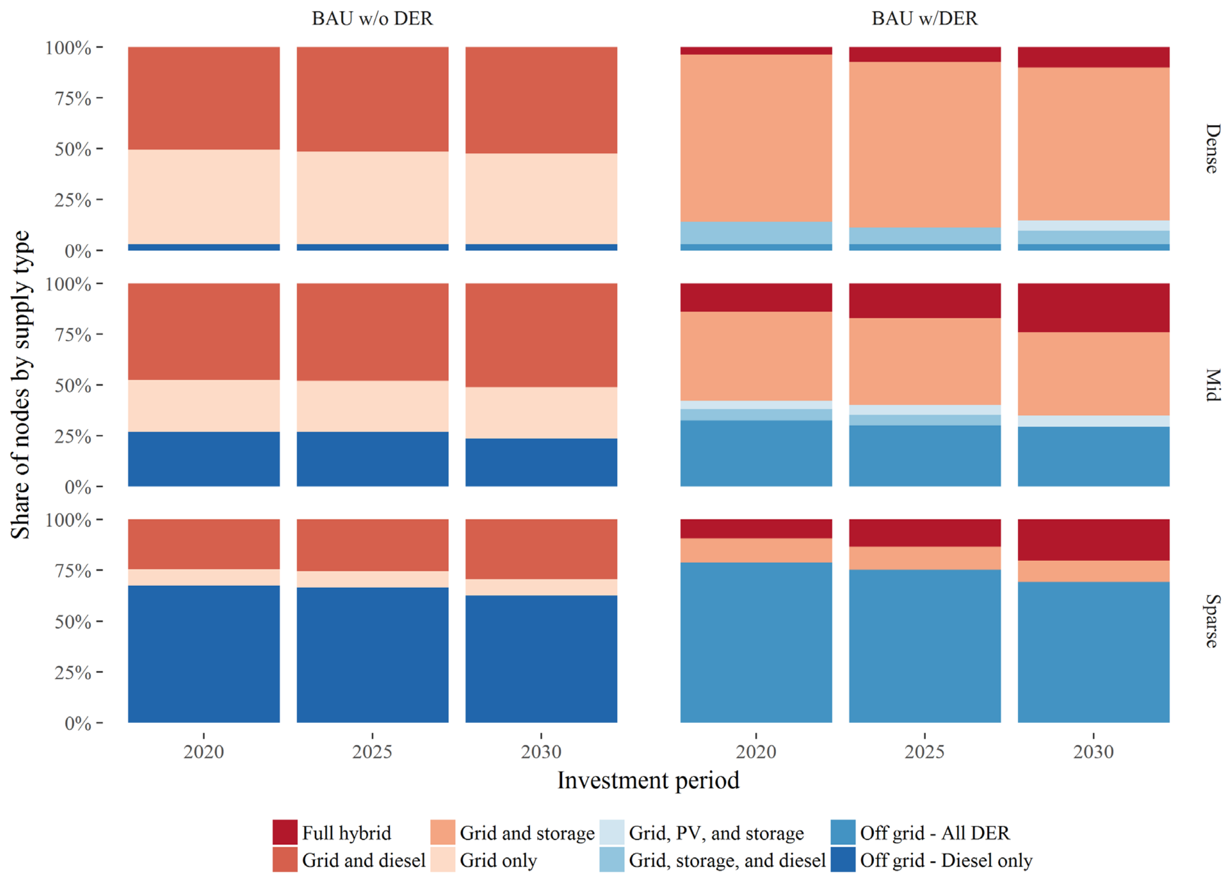

Figure 3.2 Share of nodes by supply mode and load zone density category for least cost expansion with (right) and without (left) new distributed technologies.

The expansion mix changes substantially with the presence of modular PV and storage systems that can be installed at the distribution level (see Figure 3.2, right panel). When affordable decentralized resources are available, there are no grid-only nodes in the simulations. Of the 60% nodes with grid connection, half have distributed storage. Nodes that install all possible resources grow from ~5% in 2020 to 15% by 2030 as PV becomes more affordable and is added to these hybrid systems. In addition, the share of off-grid nodes increases slightly from ~20% to ~25%. As opposed to the "traditional" expansion scenario, these nodes are supplied by a mix of PV, storage, and diesel generation. The similarity in share of off-grid nodes suggests that the decision to connect nodes to the grid depends largely on topology rather than technology alternatives. We examine this hypothesis in more detail later in this chapter when performing sensitivity analysis.

Storage availability and operation is particularly critical in shaping these new power systems. In sparse and medium density areas batteries are used to store PV production at high irradiance hours and to release in the evening (Figure B.2). In sparse areas, about 90% of peak demand is met with storage discharge. However, in dense areas storage is charged at night from the grid and released through the day to meet up to 30% of evening peak demand. This mode of operation influences the decision variable for storage discharge duration. There is a mean of 5 hours of storage in high-density areas and 2 hours of storage in medium density and sparse areas, which correlate with the optimal storage dispatch in each area.

C. Distance to the transmission system is correlated with nodal supply mix

We study the correlation between the electrical distance of a given node to the header and the type of supply mix for that node for the scenario with DER (Figure 3.3). For illustrative purposes, we use a minimum spanning tree to assign a distance to nodes that are not connected to the distribution grid and include them in this analysis. We find a relatively clear median distance threshold for each of the three supply modes and load zone density categories. Clean hybrid nodes are usually located within 50-70 km of the head node on all three density categories. Hybrid nodes – nodes supplied by a combination of grid and all DER including diesel – are more prevalent at distances of 70 km in dense areas and 100-150 km in medium and low-density areas. Off-grid nodes only become cost effective at median distances above 200 km from the feeder head, although there are off-grid nodes located as close as 120 km in medium and low density areas.

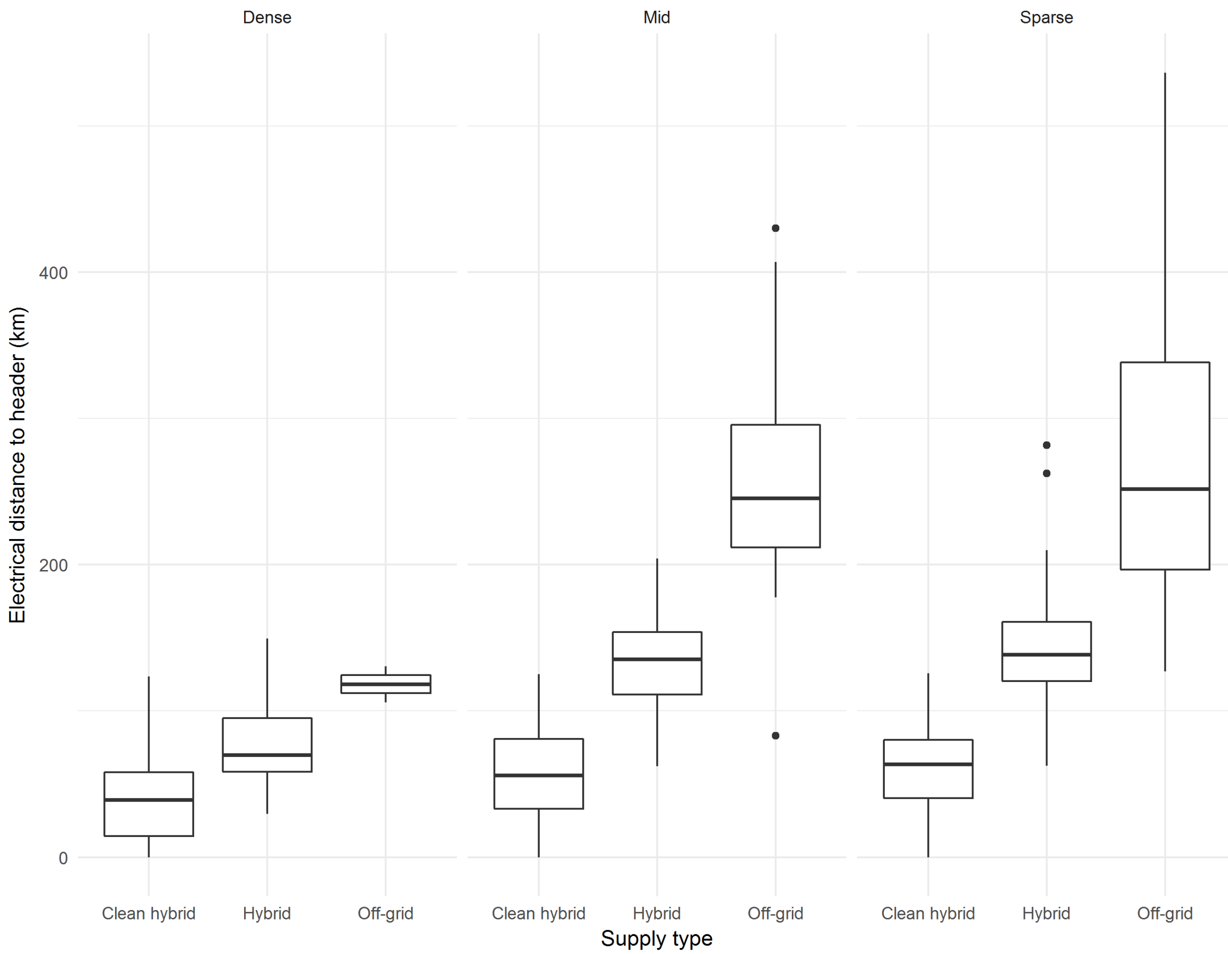

Figure 3.3 Supply mix for three categories for load zone density as a function of distance to the feeder header.

One possible explanation for the supply-distance relationship is that closer nodes can be reached by larger capacity grids that are economically dimensioned to meet peak demand. For nodes located at longer distances, it becomes more cost-effective to meet peak demand locally with a mix of dispatchable diesel and storage and build grids with less capacity that are operated with higher load factors. We find evidence of this by examining the link utilization factor (LUF)[7]. In systems with no DER, LUF for nodes farther from the head node is lower than LUF for closer nodes. However, in systems with substantial deployment of distributed resources LUF is higher for links farther from the head node (Figure B.6). This is because when DERs are available, distribution system links are sized to carry baseload from the grid and locally deployed DER are used to meet peak demand.

The electrification studies within the energy access literature have focused on thresholds to declare areas as off-grid and suggested share of population or load that would be more efficiently served off-grid. Reference (Zeyringer et al., 2015) reports that 15% of total electricity is delivered through off-grid systems in their simulations for Kenya. Reference (Deichmann et al., 2011) find that less than 10% of households could be cost-effectively supplied by decentralized solar PV in a case study for Ethiopia. Reference (Parshall et al., 2009) find that in a full penetration scenario for Kenya, 7% of households would be supplied off-grid. None of these studies allowed for hybrid systems, nor do they simulate transmission and generation capacity expansion. In the GAP model about 31% of nodes are supplied off grid when DER are available and 26% of nodes are supplied off grid when distributed solar PV and storage are not available. The difference is because distributed PV and storage are more cost-effective than diesel, which makes their joint deployment in hybrid supply modes a least cost solution. Off-grid nodes are more common in lower density areas than high-density areas. Nodes are off-grid when located beyond 100 km in low-density zones and 150 km in medium density zones, with no off-grid nodes in high density zones. This is explained by the relatively higher demand and shorter inter-nodal distance in medium density zones compared to low density zones, which makes grid extensions relatively more cost-effective in the former.

The sequencing of electrification decisions is a unique feature of GAP that highlights the relevance of system expansion dynamics in regions with low electricity access. As a case study, we study a low-density zone and map the modes of supply and grid extension decisions for a least cost scenario with perfect reliability (Figure 3.4).

[7] The LUF is the ratio of average demand to line capacity for a given line segment, in an equivalent way as load factor is defined for loads. The LUF is used to measure the efficiency in line segment utilization.

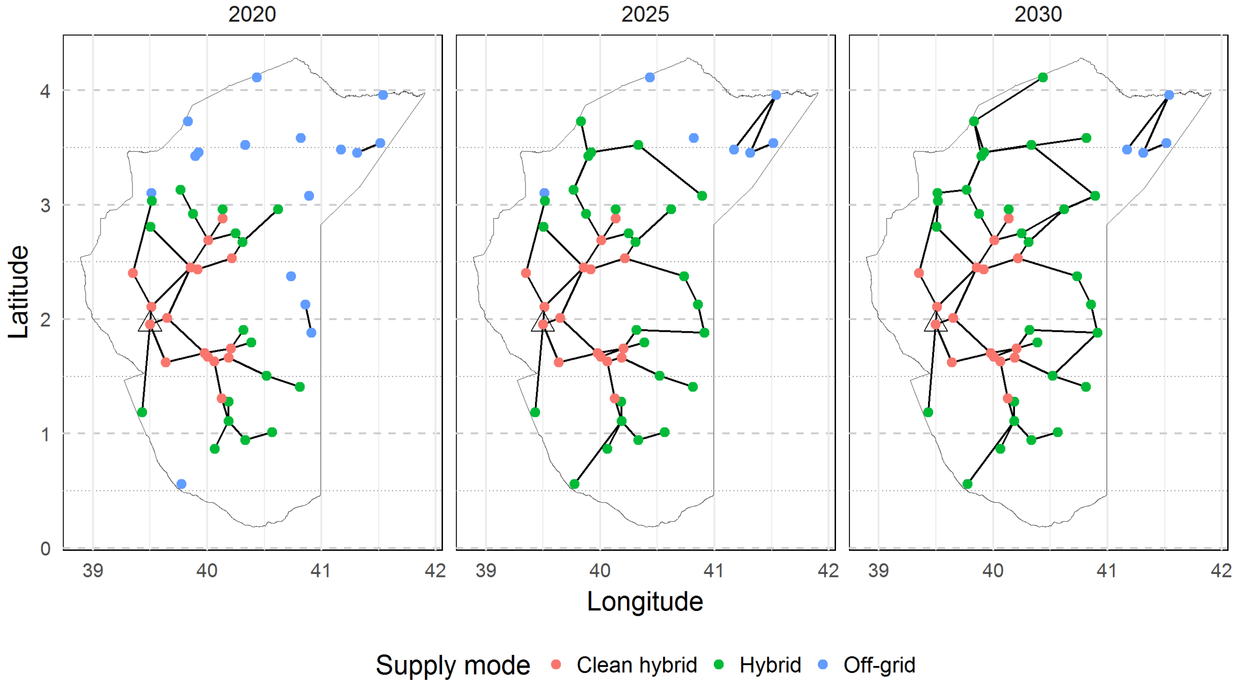

Figure 3.4 Electrification sequencing decisions for a low density load zone in northeast Kenya.

In the first period (2020), about two thirds of the nodes are connected to a distribution system; the remaining third operates in off-grid mode with PV + storage + diesel systems. There are two minigrids built that interconnect two nodes in isolation. The grid connected nodes closest to the feeder head have only distributed storage installed. Farther connected nodes have PV and storage, and the nodes at the edge of the distribution system have additional diesel generators. This is a strategy to save on losses and grid capacity for nodes that are distant, especially because distant nodes require all the system to be sized to meet their demand. The next period (2025) is characterized by grid extensions with little change in node-level supply modes. Most off-grid nodes with the full portfolio of distributed resources are integrated to the grid. The northernmost nodes are now interconnected in a larger 4-node minigrids system. By 2030, PV is installed on a few grid-connected nodes and all nodes but the small minigrids are connected to the central grid.

D. Adoption of DER increases distribution system efficiency through capital deferments

Grid topology for systems that evolve based on distributed resources is very different from a traditional system. To measure this, we compare the LUF between the "traditional" expansion scenario and the one where distributed resources are allowed. We find that grids with distributed resources are remarkably more efficient than grids without these resources, particularly in low-density areas (Figure 3.5). Median LUF for low-density systems with PV and storage is ~80% compared to ~25% in traditional systems. This is due to the shorter and reduced capacity networks and higher reliance on off-grid systems. Median LUF in high density areas are about 10% higher when distributed PV and storage are allowed compared to the traditional expansion. Higher utilization factors generally translate to more efficient use of capital, which is critical in SSA countries that suffer from capital scarcity (Shirley and Attia, 2017).

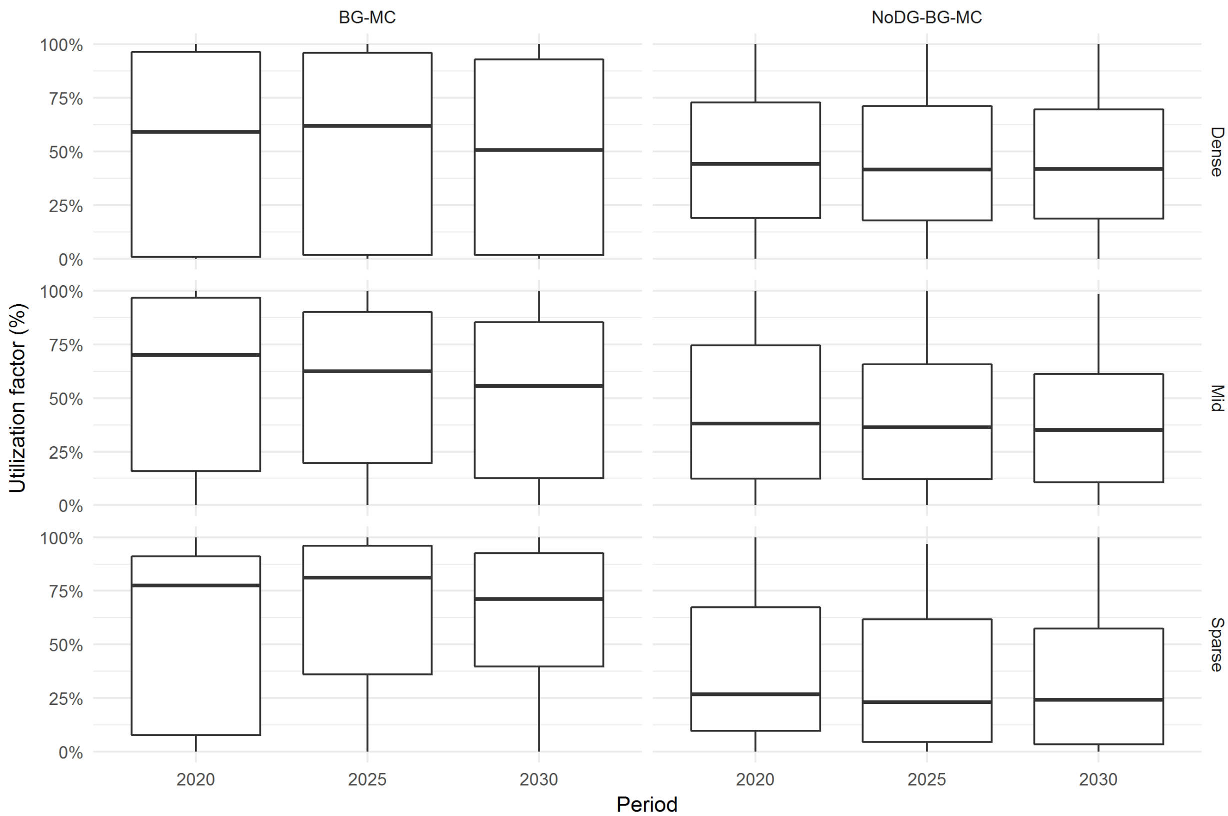

Figure 3.5 Link utilization factor for least cost scenarios with PV and storage (left) and without them (right).

E. Relevant trade-off between transmission expansion and distributed resource deployment

Transmission expansion is substantially affected by the deployment of distributed resources, since the latter replace utility scale generation that uses transmission to reach load centers. In the "traditional" scenario, national level transmission capacity is 140% larger than in the distributed resource scenario by 2020 and 84% larger by 2030. This reflects that distributed resources have important capital avoidance effects in the transmission system. The declining ratio – from 140% to 84% - responds to a faster increase in distribution circuit length and capacity in the scenario with distributed resources. These allocation decisions across the power system's value chain have relevant cost implications that we analyze later in this chapter.

The generation capacity expansion decisions for the models without modular PV or storage are very different when compared to scenarios that include these technologies (Figure B.7). Utility scale generation installed capacity reaches about 12 GW by 2030 and decentralized generation about 4 GW by 2030. In the scenario with distributed PV and storage, decentralized capacity reaches over 17 GW by 2030, 60% in PV and 35% in storage. Utility scale mix is unchanged, but installed capacity decreases to 9 GW by 2030. There is 10 to 15 times more distributed storage installed than utility-scale centralized storage. We test the effect of the system losses parameter on this ratio in the sensitivity analysis section.

F. A system that integrates DER and grid extensions is more cost effective than one that does not

The average cost of power or LCOE for the "traditional" expansion is 140 $/MWh across the simulation period. Costs include annualized investment, fuel, other variable and fixed costs, and maintenance expenditures for generation, transmission, distribution and distributed resources. The share of costs for centralized generation is 25%, for decentralized generation 45% (almost all fuel costs), and for the distribution grid is 24% (Figure B.5). The inclusion of modular PV and storage substantially reduces the average system LCOE to 103 $/MWh across the simulation period. The assumptions are a DER PV cost of 2.3 $/kW and 1.9 $/kW and DER storage cost of 460 $/kWh and 300 $/kWh in 2020 and 2030, respectively. Costs are 23% lower in the first period and 29% lower in the last period, driven by expected lower capital costs for both modular technologies. Installed capacity for distributed diesel falls from 4 GW to 1 GW in 2030 when PV and storage are available. The capacity factor of distributed diesel decreases from 40% to 29% with PV and storage, which is consistent with fuel savings by using capacity only in peak hours. The power system cost structure changes with the addition of modular PV and storage. There is an important shift from fuel expenditures to capital cost expenditure in the distribution sector, as PV and storage replace diesel generation. In this new scenario, 37% of system costs are capital investment in distributed resources and about 20% investment in the distribution grid. There is a ~20% reduction in utility scale generation investment and a ~40% reduction in distribution grid investment. Only 13% of system costs are variable, compared to almost 50% in the "traditional" scenario. Overall, distributed diesel expenditure decreases from $39 billion to $7 billion through the simulation horizon, an 85% reduction.

3.6 Sensitivity analysis

GAP model results may be sensitive to several parameters and assumptions. Through our analysis, we identify four key assumptions that we test: distribution system losses parameter; distribution grid extension costs; battery storage lifetime; and distributed storage and PV capital costs.

A. Losses (distribution system efficiency)

GAP model represents losses through an efficiency parameter set at 15% loss per 100 miles of distribution line instead of resistive and reactive line losses. The model then implements a transportation model instead of a power flow due to computational constraints. Technical and non-technical distribution system losses are very high in SSA, reaching up to 50% in some cases (Kojima and Trimble, 2016). It is important then to test the impact of distribution system's loss reduction in the expansion and operation of the whole value chain.

We test three alternative parameters at 3%, 5%, and 10% losses per 100 miles of distribution line over the system that allows distributed PV and storage (Figure B.9). The loss parameter does not affect utility-scale generation installation, but does impact distributed resource deployment. About 11 GW of distributed resources are installed by 2030 with the 3% parameter, increasing to over 15 GW with the original 15% parameter. This result is intuitive: as the grid is less efficient, larger deployment of distributed resources to meet demand at the node level becomes more cost-effective. Losses levels have an effect on the optimal supply mode decisions and the threshold distances for transitioning into different supply modes (Figure B.10). A detailed account of the losses sensitivity analysis is included in the Supplementary Information.

B. Distribution grid extension costs

Distribution grid extension costs vary considerably across regions within a country. The reference cost of 35 k$/MW-km used in the GAP model comes from actual rural electrification projects developed in Kenya in the 2008-2010 period. However, costs may be lower in denser or more central areas, or they may decrease in time with learning rates. Treating the 35 k$/MW-km as an upper threshold, we test three lower grid extension costs that we apply to the whole region: 2, 10 and 20 k$/MW-km.

We first study the impact of grid extension in supply mode. We hypothesize there may be a substitution effect between grid extensions and distributed resource deployment. Results show that for high density areas the grid extension cost have little to no effect in the supply mode (Figure B.12). Grid connected nodes with distributed storage is the predominant supply mode for high-density nodes. At very low extension costs, medium density area supply mode is similar to high-density areas. However, as extension costs increase there are more nodes with grid-connected distributed PV and diesel.

The grid extension cost threshold that defines on and off grid nodes seems to be highly non-smooth. Even at 20 k$/MW-km there are less than 3% off-grid nodes in medium density areas, compared to over 25% in the 35 k$/MW-km scenario. This suggests the existence of a tipping point in that cost range. In contrast, there is a base level of 25% of off-grid nodes in low-density areas, regardless of extension cost levels. This suggests that electrification decisions in medium density zones are more sensitive to expansion costs, but that off-grid supply in sparse areas depends mostly on topology and not the economics of grid extensions.

Lower extension costs lead to reduced adoption of distributed resources and increased installation of utility scale resources, including transmission capacity. We estimate an increased adoption of 0.5% to 0.8% of utility scale resources for each 1,000 $/MW-km reduction in grid extension costs. At the utility scale, lower distribution grid extension costs have a disproportionate impact on wind resource adoption compared to geothermal, storage, natural gas and diesel technologies. There is 75% more wind capacity in the 2 k$/MW-km scenario compared to the original 35 k$/MW-km. This is due to wind cost-effectiveness but also to higher demand levels and diversity at the transmission level that facilitate wind integration. At the distributed scale, lower extension costs lead to significant reductions in solar PV and diesel, but moderate reductions in distributed storage. This is due to the higher flexibility of storage to be used in grid connected and off-grid applications, particularly in the Kenya system with a large presence of a low cost baseload resource such as geothermal energy.

C. Battery storage lifetime

Chemical storage capacity can degrade relatively quickly under high cycling patterns, especially when used for ancillary services (Alam and Saha, 2016). We cannot make lifetime of the battery depend on its operation in a linear model like GAP, but we can test the impact of a shorter battery lifespan in the economics of this technology. We run a scenario with a 3 year lifetime (instead of the original 15 years) based on anecdotal evidence that this would be the minimum lifetime of intensely cycled battery systems.

Battery storage useful life reduction leads to an increase of the relative costs of this technology compared to other alternatives. Total system costs are ~12% higher with lower distributed storage useful life. Cost increase is driven by higher adoption and dispatch of distributed diesel generation, which in turn responds to reduced storage capacity especially in medium and low-density areas. As distributed storage is relatively more expensive, about 50% less storage capacity is installed in 2020 compared to the original scenario. Distributed PV capacity also decreases by the same ratio, which reflects the interdependency of these technologies. GAP compensates the reduction in storage capacity and PV production with increased diesel generation at the node level, plus 5% to 10% increments in capacity at the utility-scale level.

D. Capital cost reductions for distributed resources

We want to test under what capital cost regimes the system will turn mostly to off-grid supply modes instead of grid-connected modes. We simulate a fictional scenario with a capital cost for PV and storage of 1000^{th} the original values and find that every single node is supplied with a combination of distributed PV and storage. This extreme and fictional simulation does confirm the model would eventually make a pure off-grid supply choice given low enough values.

We define a set of plausible alternative capital cost reduction pathways for distributed PV and storage. We employ the most optimistic cost reduction pathways in our source data (Cole et al., 2016; Mayer et al., 2015). The original 2030 distributed PV cost is 1.9 \$/W and the new cost is 1 \$/W. The original 2030 distributed battery storage cost is 112 \$/kWh and the new cost is 90 \$/kWh. We find that these lower capital costs do not lead to more off-grid nodes, but to more hybrid grid-connected nodes that now include PV and diesel. The share of off-grid nodes stays around 25%-30%, similar to the share with the original capital costs.

We do find that the size of the distributed PV systems installed and the energy produced by them changes substantially with these lower costs. The national level energy balance shows that about 50% of electricity is sourced from distributed PV by 2030 in a scenario with low PV and storage costs, compared to 25% in the original scenario (Figure B.13). We estimate median node installed capacity for each distributed technology. We find that in low-density areas the median storage and PV system size barely changes in the new scenario with lower capital costs. However, in medium density areas and high-density areas the median PV system size increases from 33 to 42 and 12 to 20 MW by 2030, respectively (Figure B.14). Interestingly, median distributed energy storage capacity decreases from 6.5 to 4 hours in dense areas when capital costs are lower. This is possibly explained by PV capacity costs declining relatively faster than storage costs (50% compared to 25%). It follows that the optimal decision is to allocate capital for larger PV systems and store fewer hours of PV production in the middle of the day rather than longer hours of grid power at night. Then, distribution system dispatch in denser areas with low DER costs mimics the low density areas dispatch patterns described before.

E. Financing rates

Higher financing costs for the electricity sector in most emerging economies are explained largely by the risk and uncertainty involved in the planning, investment, and operation of these markets. This is particularly true for DER, because these technologies are relatively young and their business cases and applications are still immature and untested. In addition, most small residential DER systems are sold directly to end users whose creditworthiness is very hard to assess, which translates into higher financing rate premiums (Babbs, 2018).

We test the impact of a very low (1%) and a very high (15%) financing rate for DER, compared to the standard 7% used throughout this study. The lower rate would reflect active intervention from the government to reduce financing rates by providing guarantees to lenders and developers, or alternatively direct subsidies to investors. The higher rate better reflects the current reality of many individual users that are poor credit subjects and pay hefty premiums.

A very low financing rate makes capital cost cheaper, which leads to an increase from 15 GW to 25 GW of DER capacity by 2030 compared to the base scenario (Figure B.12). About 80% of this growth is in distributed solar, and the remaining in distributed storage. In contrast, a very high finance rate causes a decrease in DER adoption to about 10 GW by 2030, again mostly in solar PV. The reduced DER capacity is partly offset by distributed diesel generation that becomes comparatively cheaper and minimal increase in centralized generation. The large capacity increase in DER adoption with a lower financing rate is reflected as well in energy consumption. With a low finance rate, about 35% of energy is supplied from DER, while in the base case this share is about 20%. This suggests that even if financing rates were very favorable to DER, the central grid would still supply about two thirds of the electricity consumed by customers in the system. Higher finance rates for DER also translate to an increase of ~15 $/MWh in average system costs by 2030, while lower rates reduce average system costs by a similar amount.

3.7 Discussion

One of the most robust results in this chapter is the predominance of hybrid supply modes – nodes that are supplied electricity by a combination of grid power and DER – when modular storage and PV resources are available. In general, the share of grid-only nodes is close to zero for all scenarios where DERs are available, regardless of the value of any of the key variables analyzed in the sensitivity runs. The most prevalent hybrid supply modes are characterized by grid connected distributed storage. In fact, across all scenarios analyzed distributed storage is deployed in 70% to 90% of the nodes. These results suggest that DER enable the development of different distribution systems compared to the traditional design paradigms and that utilities should design their systems in including DER deployment from the onset. The actual decision point is not whether to supply a given node from centralized or decentralized resources, but the relative balance of the capacity of centralized and decentralized modes of supply, including the distribution and transmission grids.

The main supply mode commonly includes central grid operating jointly with storage and/or PV systems. Policy makers and utilities should consider that the joint deployment and operation of these three resources is more efficient than their individual deployment. This has an impact on the design of adoption targets that are focused on a single resource such as the California storage mandate or rooftop PV adoption targets. Our results suggests that policies should focus on fostering hybrid systems in denser and higher consumption areas, and off-grid multi-resource systems – diesel, storage, and PV – in specific sparser locations. Results also show how relevant it is to design these systems to be grid ready. Analyzing the sequencing of deployment in low-density areas suggests that nodes can be initially supplied in off-grid modes but later connected to an expanding distribution grid. This strategy may also have relevant impact to accelerate electricity access in countries with high number of unconnected households. Sequencing of DER and grid extension supply modes shows that distributed resource expansion is integral to meet load with high reliability levels.

We find that including existing transmission and generation assets in the simulation made no difference in the electrification pathways. This suggests that sunk costs from existing infrastructure have little to no influence on the evolution of undeveloped power systems. It follows that new investments will shape the future power systems in these regions. Another important consequence is that data for existing transmission and generation assets may not be critical to develop electrification pathways. This is important for developing and calibrating bottom-up models like GAP that require large amount of data and that can benefit of an understanding of what data is more relevant. However, whether this conclusion applies to the distribution system is outside the scope of this chapter, as data for this segment is not publicly available for testing.

The GAP model is unique in its ability to represent the whole value chain expansion, including generation and transmission. This may explain the relatively higher share of off-grid nodes of 25% across most scenarios compared to 10%-15% from results in previous studies. The share of off-grid nodes is relatively insensitive to most variables including grid extensions, capital cost reductions, and financing costs, but it is sensitive to distribution system losses. As the distribution system operates more efficiently – with reduced losses –, the share of off-grid nodes declines substantially. It is also notable that lower DER costs do not affect the share of off-grid nodes, but do affect the installed DER capacity especially in dense area nodes. Then, the design of strategies for universal access should not be contingent on potential declines in the costs of DER, but relate to the performance of the distribution system.

The trade-off between losses and number off-grid nodes highlights a relevant design challenge. Utilities could invest in reducing distribution system losses by developing higher capacity systems and performing a more efficient commercial operation to reduce non-technical losses. In doing this, utilities would be shifting investment from DER to the distribution grid infrastructure and utility internal processes. Alternatively, utilities could operate higher losses systems by investing more in DER to reduce the cost effect of lost power. This decision will depend on how expensive it actually is to reduce technical and non-technical losses. A reduction in loss parameter from 15% to 3% per 100 miles translates into a 12 $/MWh decrease in average system costs of. This is equivalent to approximately 1 $/MWh per % reduction. If the cost of reducing technical and non-technical losses is above this value, it may be more beneficial to deploy more DER instead of expanding the distribution grid.

The inclusion of DER has important capital deferment consequences along the value chain, but particularly in the distribution system. We find about 40% cost reduction in the distribution grid when DER are available compared to when DER are not available. This reduction in costs comes from decreased distribution link capacity, which is explained by links being sized to transport baseload demand rather than peak demand. Peak demand is met by integrating grid power with a combination of PV, storage, and diesel generation sourced at the node level. This result suggests that undeveloped systems should actively integrate DER, demand response, and other mechanisms into their design process to avoid overbuilding the distribution grid. In addition to capital and maintenance savings in distribution systems, deployment of distributed resources may have relevant reliability consequences. For example, a higher number of circuits located in sparse areas can lead to less reliable systems with more failure points and longer interruptions (contingent to the reliability of the distributed resources). This is because a system with shorter and more concentrated circuits in sparse areas will be maintained at lower costs and may be recovered faster when outages occur. In denser areas, more meshed systems may be more resilient and redundancy may improve reliability parameters (Celli et al., 2004). A power system with high penetration of DER has comparatively lower variable cost and higher fixed costs than a system that has low penetration of these resources. This new cost structure can have relevant consequences. First, it decouples power system economics from the volatile price swings of fossil fuels, particularly diesel. Reduced dependence on distributed diesel generation will improve reliability due to a decrease chance of fuel shortages that commonly affect remote areas. Second, larger capital expenditures will require much more active and novel financing mechanisms to attract enough capital and to assess the new types of risks that correlate with DER investments. Third, these findings highlight the relevance of ownership decisions for distributed resources, as their optimal deployment may reallocate significant capital away from the traditional utility should these assets be owned by private actors. Finally, a capital-intensive cost structure raises questions about the continued application of volumetric rates when almost 90% of power system costs are fixed[8].

Financing mechanisms will have an important impact on the ability of utilities, regulators, and governments of developing high DER penetration power systems. Our findings comparing very low and very high financing rates for DER suggest that for every percent point increase from the standard financing rate there is roughly 6% less DER capacity deployed and a 2% increase in system costs. Financing costs for DER have a direct impact in distribution system capacity sizing, as a system with lower financing costs and more DER deployment requires half the capacity in distribution links compared to a system with higher financing costs. Lowering financing costs does not only reduce prices, but could lead to the development of a type of distribution system much more intensive in DER and very different from the "traditional" expansion pathway.

The deployment of storage reflects that its main purpose is to provide flexibility to the grid and to maximize the efficiency or utilization of the distribution lines. The number of nodes with storage increase as distribution losses is reduced, which reflects that storage becomes more valuable as its charging from the grid becomes less expensive due to higher distribution system efficiency. This finding would support the development of policies that encourage centrally dispatched distributed storage adoption. The GAP model cannot simulate the effect of storage if it was managed by each individual node or user, but the dispatch patterns suggest there may be system level benefits to a centralized management of storage asset dispatch.

[8] This result is relevant for Kenya given the high volumes of geothermal and wind power that composes the optimal central system expansion. However, it is expected that power systems around the globe will transition to be supplied by technologies with low or zero variable cost to meet decarbonization targets.

Supply modes are relevant to understand grid design, but the DER capacity choice better characterizes grid operation and highlights a few of the critical features implicit in the GAP model. The size of storage increases substantially as load zones get denser, because storage is charged mostly from the grid and used to meet resource adequacy requirements. This result is possibly contingent on the fact that GAP makes centrally optimized dispatch decisions for distributed storage to achieve system level least cost operation. In most existing applications, behind the meter storage is managed by the owner to maximize their benefits subject to opportunities offered by net-metering, net-billing, or other policies. The widespread application of distributed storage in GAP may importantly depend on the ability of future distribution system operators (DSOs) to dispatch storage units located in their systems. In addition, node level investment and operational decisions in the GAP model depend on the availability of locational marginal prices (LMP) at the distribution level.

Until recently, the integrative planning approach of the GAP model had no comparable regulatory process. In most jurisdictions, integrated resource planning (IRP) covers generation and transmission alone, with distribution planning being an independent process (Kahrl et al., 2016). However, in recent years distribution planning has evolved to actively integrate DER, and IRP in some U.S. states is requiring a treatment of DER equivalent to supply side resources (Schwartz and Frick, 2019). These changes are being driven by the cost, resilience, reliability, and flexibility benefits brought by DERs, and may benefit from the coordination and high-level perspective from a model like GAP. In particular, the resilience benefits of DER may be substantial, but research is needed to produce resilience valuation frameworks useful for regulators (Rickerson et al., 2019).

Finally, expansion pathways generally do not change much between periods. 2020 investment choices do differ substantially across scenarios, but they do not change significantly for 2025 or 2030 for the same scenario. This may be driven in part by the lack of dynamism in most variables, with the exception of DER capital costs that decline during the simulation period. Including cost reductions over time for grid extensions or improvements over time in system efficiency could produce higher temporal variation. As is, these results suggest that electrification pathways are largely defined early in the investment periods and that there may be benefits to earlier and more aggressive action to develop systems that are heavily based in DER and that use hybrid supply modes. Starting with a "traditional" expansion with the expectation to transform the system later to adopt DER may be an expensive route with high risk of unused legacy distribution system assets.

Chapter 4

Measuring and assessing the Kenyan electrification process in 2006-2016

4.1 Introduction

Sustainable Development Goal (SDG) #7 strives to "ensure access to affordable, reliable, sustainable and modern energy for all" (UN, 2015, p. 14) based on the recognition that access to electricity is a fundamental precursor for wellbeing in modern societies (Ghosh Banerjee et al., 2014). SDG #7 gave an important push to electrification processes worldwide, but particularly so in Africa and Asia where the vast majority of unconnected population live. Recently, there have been calls to action to improve the pace and breadth of electrification processes, with a focus on new business models (Power for All, 2019). These authors argue that the mainstream electrification strategy of extending the grid to unconnected populations and intensifying connections in areas with access falls short of being a universal strategy. It follows that research on actual outcomes of the electrification process is required to drive possible changes to these strategies.

There has been substantial research on the determinants of electricity access and energy consumption patterns, which were presented in the introductory chapter in this dissertation. Generally, this literature finds that variables such as income and education correlate with preference for higher energy quality carriers. However, most of this literature takes a cross-sectional approach that cannot capture the pace and breadth in electrification expansion. A few papers have used longitudinal data to track this metric. For example, (Rao and Pachauri, 2017) use electricity access and income data from the World Bank to trace the pace of electrification in LEA countries from 1990 to 2010. (Andrade-Pacheco et al., 2019) blend several spatially explicit datasets to track the probability of electricity access in Africa from 2000 to 2013 and report estimations for access levels. (Shrestha et al., 2004) study the electrification processes in Bangladesh and Tanzania and conclude that investment resources, generation capacity and economic growth were key drivers. None of these papers analyzed the role that rural-urban migration could play in increasing access by bringing population close to areas with access, rather than the grid to areas with unconnected population.

Studies mentioned before have employed simplified definitions of electricity access, or relied on an externally sourced metric for access. However, appropriate measures of energy poverty are scarce and incomplete (Pachauri and Spreng, 2011). Measuring electricity access properly requires complex multi-criteria indicators (Groh et al., 2016). Availability and affordability of electricity hampers consumption and should be incorporated in broader metrics for access (Taneja, 2018). For this reason, this chapter focuses on two related empirical questions. First, it explores three different definitions for electricity access in Kenya using microdata from household budget surveys. Outcomes and drivers of electrification are reported for these metrics. Second, it uses one of these metrics and explains how much of the gains in electrification have come from grid extensions versus rural-urban migration. I find that using electrification metrics that track an end-use such as lighting could increase by 50% the measure of population that has access to an electrified end use, compared to a simplified metric of connection to the grid. I report ample spatial heterogeneity of connection across Kenya, which has been decreasing over time. Finally, I find that rural-urban migration explains about 45% of the gains in the share of population with access to electricity, while grid extensions explain about 50% of these gains.

The electricity sector in Kenya is divided in three segments – generation, transmission and distribution, all with heavy state involvement. Rural electrification is spearheaded by the Rural Electrification Authority (REA) established in 2006. However, actual deployment and operation of grid connections is performed by Kenya Power, the sole distribution company, and the REA only develops small and targeted off-grid systems. In 2015, the African Development Bank and the World Bank implemented the Last Mile Connectivity program to focus on intensification of existing infrastructure by subsidizing and financing service extension for houses 600 meter or less from a transformer (SHE-KPLC, 2014). The Government of Kenya set a 70% electrification target by 2017 and universal access by 2020. While the Government asserts that it has met the 2017 target, the veracity of the measurements has been subject to scrutiny and criticism (Wafula, 2017).

4.2 Methods and data

A. Data sources

The analysis and results in this chapter are based on the two most recent Kenya Integrated Household Budget Surveys (KHBS) developed in 2005/2006 and 2015/2016, referred for simplicity as the 2006 and 2016 surveys hereinafter, respectively. The surveys were designed to capture data that would be used to update poverty, welfare, and employment statistics, derive the consumer price index, and revise national accounts structuring. The surveys collect data on household- and individual-level socio-economic variables such as education, health, energy, housing, water, sanitation, agriculture and livestock, enterprises, and expenditure and consumption. The survey sample sizes are reported as follows:

- The 2006 survey was conducted between May 2005 and April 2006 over 1343 randomly selected representative clusters, each one with ten randomly selected households that were subject of the study. The total sample is then 8610 rural and 4820 urban households. The sample is designed to be national and sub-nationally (district level) representative. More information can be found on the 2005/2006 KHBS Basic Report (KNBS, 2007).

- The 2016 survey was conducted between September 2015 and August 2016 over 2388 representative clusters, each one with ten randomly selected households that were subject of the study. The total sample is then 14120 rural and 9888 urban households. The sample is designed to be national and sub-nationally (county level) representative. More information can be found on the 2015/2016 KHBS Basic Report (KNBS, 2018).

As indicated, the minimum unit of analysis in the survey is the household. However, the publicly available datasets only report household location at the district or county level. I use household level data for cross-sectional analysis. To track changes over time, I create a pseudo-panel data structure following Deaton (1985) by integrating 2006 and 2016 county-level indicators in a repeated cross section to run regression analyses. Finally, in all analyses, sample weights are used to calculate population-level statistics.

This chapter also uses spatially explicit electricity access data derived from nightlights developed by Andrade-Pacheco et al. (2019). In this paper, the authors blend survey data, nightlights satellite imagery, land cover data, and geostatistics modeling to produce 5 km resolution maps for electricity access in Africa from 2000 to 2013. Using this model, they predict the probability of a household having electricity on each 5 km grid. I downloaded their resulting raster data – one Africa map per year from 2000 to 2013 with about ~28,000 grids each – and processed the grids for Kenya to extract the probability [0,1] of a given grid to have electricity. This data are used as a proxy for distribution grid extensions to rural areas over time. I must note the inconsistency between the most recent year for this data, 2013, and the second cohort in our analysis, 2015/2016. This gap could have a relevant impact in the analysis considering the push for electrification spearheaded by the government and utility during that time (Taneja, 2018).

Finally, this chapter also employs distribution transformer installation data provided by Kenya Power. The original data holds over 57 thousand distribution transformers installed across Kenya. Fifty-one thousand of these transformers have recorded installation date and location. I extract the stock of rural transformers as of January 2006 and January 2016 to match approximately the middle of each KHBS survey. I use the total number of rural transformers installed in each vintage by county as a proxy for grid extension and as an alternative to the nightlight based data described before.

B. Methods

This chapter uses the two KHBS surveys to provide an overview and descriptive statistics of the electrification progress in Kenya for the last 15 years. To make the surveys comparable, I developed a mapping between the 70 districts that were the main administrative division in 2006 and the 47 counties that exist since the 2010 Constitution (and hence reported in the 2016 survey). The district to county assignment is n-to-1 and districts are straightforwardly grouped into counties[9]. Using this approach, I am able to report data consistently for the current 47 Kenyan counties.

This chapter employs regression analysis to understand the contribution of different variables to the growth in electricity access in Kenya from 2005 to 2016. To explore this particular issue, I implement a Oaxaca-Blinder (O-B) decomposition to understand how much of the variation in the outcome variable – county-level electrification rates – is due to either changes in variables that influence the connection decision or changes in the sensitivity of electrification rates to these variables.

The O-B decomposition was created independently by Blinder (1973) and Oaxaca (1973) as a way to disentangle the sources of differences across two cohorts. For example, the labor economics field employs O-B decomposition to understand sources of differences in wage levels among

[9] The only exception to the direct assignment is the former district of Thika, which was divided between the counties of Muranga and Kiambu. I assigned Thika to Kiambu because the majority of the land and main cities in the Thika district were overlapping with Kiambu county.

groups differentiated by gender or race. The two-fold O-B decomposition splits the difference in outcomes in two terms (Hlavac, 2018):

$$\Delta\bar{Y} = \underbrace{(\bar{\boldsymbol{X}}_A - \bar{\boldsymbol{X}}_B)'\hat{\boldsymbol{\beta}}_R}_{\text{explained}} + \underbrace{\underbrace{\bar{\boldsymbol{X}}'_A(\hat{\boldsymbol{\beta}}_A - \hat{\boldsymbol{\beta}}_R)}_{\text{unexplained A}} + \underbrace{\bar{\boldsymbol{X}}'_B(\hat{\boldsymbol{\beta}}_R - \hat{\boldsymbol{\beta}}_B)}_{\text{unexplained B}}}_{\text{unexplained}} \tag{4.1}$$

In equation 4.1, the subscripts A and B correspond to the cohorts, and R corresponds to a reference group that can be formed by weighing A and B in different ways.[10] The explained term captures the impact on the outcome of changes of a given variable across groups. For example, assume that one is examining two racial groups, that the outcome is wage levels, and that the variable of interest is work experience. The explained term would capture how much wage difference is attributed to differences in work experience across the two groups. The unexplained term would capture differences that are not attributable to work experience. Technically, this term measures the impact on the outcome of changes in the regression coefficient across groups. In this example, the unexplained term may suggest that a fraction of the gap in wages might be due to discrimination, although it can also reflect the impact of unobserved variables. The unexplained term can be divided further in the portion that relates to group A, and the one that relates to group B.[11] The reference regression coefficient, β_R, is calculated from the whole sample following different methods. The advantage of the O-B method is that it quantifies the share of the change in the outcome (e.g. wage level or electrification rates) that is attributable to specific explanatory variables, or that remains unexplained. A formal explanation of the O-B decomposition method can be found in Jann (2008).

The O-B decomposition has been used in a few energy studies to estimate the impact of demographic and preference changes on energy consumption (see Levinson, 2014; Morikawa, 2012) and to explain changes in trends on private investment in energy efficiency (Carvallo et al., 2019). In this chapter, I follow the insight from Leard et al. (2019) and García-Altés et al. (2011), and assign an older and a newer vintage to each of the two cohorts. This way, the explained portion will capture the share of change on electrification rate that can be attributed to three possible drivers: grid extension, rural-urban migration, and income.

4.3 Results

In subsections 4.3.A through 4.3.C, I present three different assessments of electricity access metrics. In doing that, I provide an overview of different aspects of the electrification process in Kenya including the role of solar energy, affordability issues for connected customers, and lighting choices.

[10] The reference is formed by weighting coefficients for the regressions of groups A and B, or by pooling both groups together and running a "reference" regression. For more details see Neumark (1988) and Cotton (1988)

[11] This split is accomplished by comparing the regression coefficient of group A and B against the reference coefficient.

A. Measuring access to electricity

The first step prior to processing the surveys is to define what will be meant by "access" in the context of this chapter. There is a recognition that measuring electricity access is complex when quality and quantity dimensions are considered (Bhatia and Angelou, 2015; Groh et al., 2016). The World Bank's Multi-Tier Framework (MTF) was developed precisely to deal with the ambiguity of access to electricity (Bhatia and Angelou, 2015). The MTF is a complex multi-dimensional set of criteria to assess access that includes quantity of electricity consumed, quality of the resource, availability, and affordability. The MTF classifies households in six different access tiers depending on combinations of these different dimensions. The top access tier resembles the consumption standards of an average upper-middle income country household. There are no known surveys regularly conducted in low-income economies that capture all the dimensions required by the MTF[12].

The KHBS surveys do capture several dimensions of electricity access, as follows:

- Whether the household is supplied by KPLC
- Whether the household has installed solar panels[13]
- What is the main source of electricity and of lighting
- Expenditure in electricity and lighting
- Consumption levels of electricity when connected to the central grid

The two surveys ask a direct question about having electricity. The 2006 KHBS asks if the household had any electricity working in the dwelling. The 2016 survey asks if the household has electricity. Although intended to be straightforward and binary answered questions, both framings have trouble. The notion of "working electricity" may be interpreted in several ways, mostly depending on the reliability of supply in the case of central grid connections or the timed supply for micro-grids and generators that operate in evening hours. The Interviewer's Manual suggests the focus is on the former. The recent survey seemingly tried to make the question more objective by asking if the household has electricity. However, it is again complex to define what "having electricity" means: is it having a connection? Is it being able to afford it? Is it being able to consume whenever, i.e. considering a reliability dimension? Is it referring to the central grid only, or to any resource? The answer to these questions may produce different interpretations of what "having electricity" may mean. This chapter explores these different interpretations of access to electricity.

The complexity in answering these questions can be illustrated by cross tabulating certain responses in each survey. For example, the main source of electricity for a household and whether the household has working electricity are reported in Table 4.1 for the 2006 KHBS. In this survey,

[12] This is why the World Bank designed and applied its own MTF survey in several countries.

[13] The question is phrased in such way that answer could include rooftop solar panels and much smaller and limited solar home systems. The number of households answering positively is much lower than the number of households declaring owning solar lighting. Then, it is likely the question is interpreted as referring to high power rooftop systems.

about 1 million (15%) Kenyan households reported being connected to KPLC and 80% of the households did not have access to the grid, with 5% reporting access through different sources. A substantial majority of the households that declared KPLC as their main source also consider they have access to working electricity. In contrast, a significant majority of the households that declare that solar panels are their main source of electricity do not consider having working electricity. While it is plausible that panels fail, it is unlikely that almost 90% of the panels in households that have them are in non-working condition. Similarly, households that report "Other" main source of electricity (generator or batteries) follow the same pattern. It is possible that these households did not consider themselves as having working electricity because they did not have a connection to KPLC. The question is whether these households should be considered as having access to electricity if their self-assessment is that their main source is not "working electricity", or if the ownership of an electricity source should be enough to declare them as having access.

Table 4.1 Household main source of electricity and their assessment of whether it "works" or not, KHBS 2006

		Main source of electricity (thousand hh)			
		None	KPLC	Solar Panel	Other
Working electricity	Yes	87	1,081	18	25
	No	5,550	6	118	140

In the recent survey, the data are consistent: all the households that declare not having electricity have no main source of electricity reported (Table 4.2). Conversely, this result can be interpreted that any household that reported a "main source of electricity" considers itself as having access to electricity. In the new survey, roughly 4.7 million households report being connected to KPLC or 42% of total Kenyan households. This figure is consistent with 4.89 million customers reported by KPLC for 2015/2016 in their 2017 annual report, which also includes commercial, industrial, and institutional customers (KPLC, 2017).

Table 4.2 Household main source of electricity and their response on "having electricity", KHBS 2016

		Main source of electricity (thousand hh)			
		None	KPLC	Solar Panel	Other
Household has electricity	Yes	0	4,738	190	25
	No	6,460	0	0	0

The second main source of electricity in Kenya used to be diesel generators (reported as "Other" in the 2006 KHBS). By 2016, most users of diesel generation had either been connected to the main grid or switched to solar energy. About 190 thousand households reported solar panels as their main source of electricity, compared to 136 thousand households in 2006. Solar panel adoption by households grew 3.4% annually on average, compared to 16% average annual growth for number of households with KPLC supply. This is largely informed by the fact that solar panel deployment is only performed by the private sector with little to no governmental support (Jacobson, 2007). Solar panel (not solar home system) deployment is almost exclusively located in rural and remote areas in Northern Kenya, where the main grid is not yet present (see Figure C.1). An important caveat to solar panel ownership comes from the number of households that report owning a solar panel in the 2016 KHBS. While 190 thousand households indicate deriving their electricity from solar panels, over 1.3 million households report owning a solar panel. This is explained by the role of solar lighting, which is explored later in subsection 4.3.C.

The notion of "working electricity" explored in this subsection may stem from the perception of users of (i) their capacity to afford consuming electricity and/or (ii) the capacity of the system to supply certain end uses. The following subsections present two definitions of electricity access based on these perceptions: affordability/availability and lighting choices.

B. Access through availability and affordability

Affordability and availability are two components of a broader electricity access definition for unsupplied, but also for supplied households (Table 4.3). Note that I use "supplied" instead of "connected" to encompass grid and off-grid sources of electricity.

Table 4.3 Understanding availability and affordability as components of electricity access for connected and unconnected households

	Has a connection to an electricity source (ability to consume power)	**Does not have a connection to an electricity source (inability to consume power)**
Availability	Reliability issues prevent households from consuming power at the times needed	The connection to a central grid or minigrid may be physically too distant, resulting in no service being offered to the household
Affordability	Fixed costs or volumetric charges may result in a bill that is unaffordable, for households with utility connection. Fuel prices may constrain operation of generators.	The grid is accessible, but households cannot afford the connection and/or wiring fees or cannot afford self-supply technologies such as generators or solar panels

The ability to consume power and hence satisfy an end-use is informed by different drivers depending on whether a household has access to electricity supply or not. For supplied households, their ability to consume power depends on the system to deliver electricity at the times when their end-uses need them (e.g. in the evening for lighting, in the middle of the day for ironing, or through the day for refrigeration). This ability then depends on how reliable the system is to provide power at those times. For these households, their ability to consume also depends on their financial capacity to cover their electricity costs, either by paying the bill, by refilling their prepaid meter, or by purchasing fuel for a generator. For households connected to KPLC, if the fixed costs are high or the unit consumption costs unaffordable it may be difficult for poorer households to consume any electricity on an ongoing basis. Aware of this, the Kenya Government defined an increasing block tariff structure that provided a "life-line" of 50 kWh/month at a very low subsidized cost, increased to 100 kWh/month in August 2018.

For unsupplied households, their inability to consume electricity is due to lack of access to a supply technology, either the grid, solar panels, a generator or others. There are still dimensions of both availability and affordability that drive this condition. Geographical distance to the closest transformer or circuit is usually the first (and formidable) barrier for households to have no electricity available to them. In the 2006 KHBS, non-supplied households were asked if they knew of any houses connected to electricity within 100 m of them. Only 15% of households in rural areas reported being within close proximity of any households with a connection, which means that the majority of rural households without a grid connection did not have physical access to it. In contrast, 75% of households without electricity surveyed in 2006 that lived in urban areas were located close to households that did have electricity supplied by KPLC. While the 2006 KHBS does not ask why these households with grid close by are not connected, the 2016 KHBS did ask for the main reason for no connection. Sixty five percent of both rural and urban households reported that the connection/wiring fee was unaffordable to them. Furthermore, 93% and 85% of the two lowest income households in rural areas report the connection fee is their main barrier for electricity access, although even half of higher income households in rural areas also report the same.

An assessment of affordability for supplied households can be made by examining the consumption levels reported by households whose main supplier is KPLC. The KHBS 2016 is used to provide a concrete example (Figure 4.1). According to the histogram, roughly 250 thousand households across Kenya reported consuming between 0 to 10 kWh in the month before the survey was administered. Similarly, about 900 thousand households reported consuming between 10 to 20 kWh per month. These results suggest that if the MTF is followed, only 77 thousand households or 1.8% of total connected households, have Tier 5 access levels. About a million households, 25% of total, consume just enough to power lights, charge phones, turn on a fan and potentially use a TV if they own one. These houses lie in the Tier 1 to Tier 3 range for consumption levels, according to the MTF, without reliability considerations that are not available in these surveys.

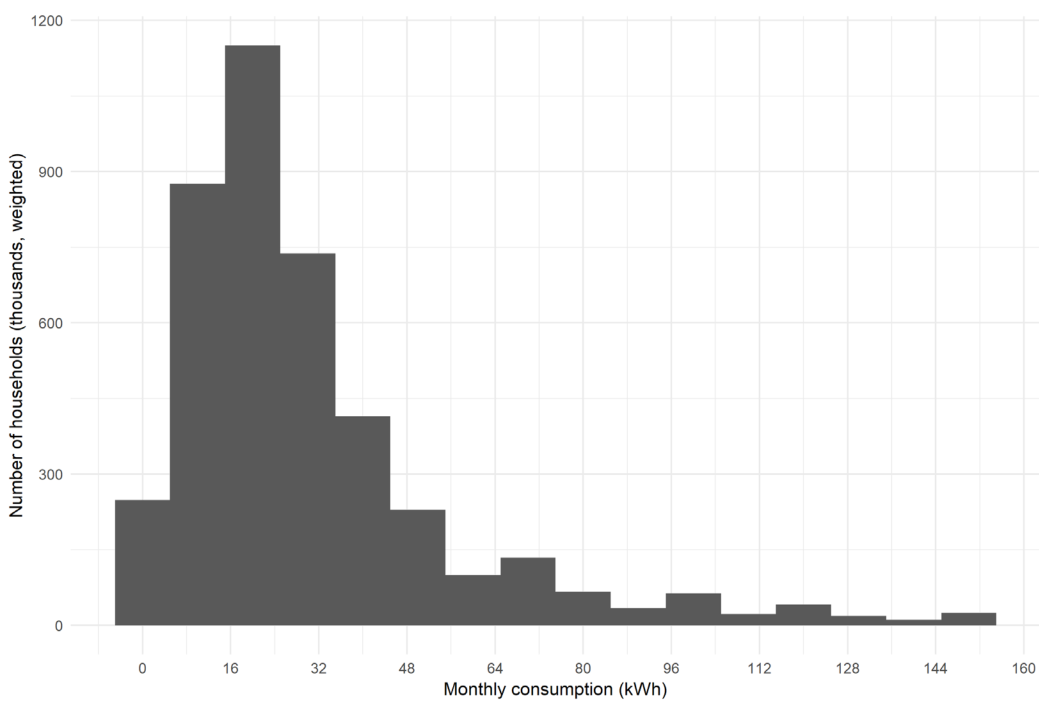

Figure 4.1 Total number of Kenyan households by consumption level, KHBS 2016.

The main message from Table 4.3 and this section is that households that are supplied by an electricity source may still be considered as not having access. A connection to an electricity supply may be understood as a necessary, but not sufficient condition for access. I challenge and reframe this definition in the next section when exploring an assessment of access through what probably is the main end-use for electricity: lighting.

C. Access through lighting choices

A third way to understand access is as meeting end uses, rather than owning a connection to or source of electricity. A good implementation of this framing is to focus on sources for lighting, usually the first end use that households want to electrify to replace tin lamps and other paraffin and kerosene based lighting sources (Alstone et al., 2015). Lighting sources may be electric, but not necessarily depend on a connection to the grid or on onsite electric generation. Torches and solar lanterns are good examples of such devices. The 2006 KHBS reports the two main lighting sources used in their households, while the 2016 KHBS reports the main source of lighting for the household. Assuming that the first mention in the 2006 KHBS is the primary source, Table 4.4 shows the number of households and share that declared using a certain type of technology as their primary lighting source. The two bold rows correspond to electrically supplied lighting, either from the grid, through a solar system, or through a flashlight/lamp.

Table 4.4 Level and share of population with access to lighting sources for the 2006 and 2016 KHBS.

	Households		Share	
	2006	2016	2006	2016
Paraffin	5,253,019	4,021,618	76%	35%
Firewood	293,044	185,591	4%	2%
Other	73,939	320,508	1%	3%
Battery Lamp/ Torch	**72,873**	**544,633**	**1%**	**5%**
Solar Energy	**112,499**	**1,611,571**	**2%**	**14%**
Grid electricity	**1,087,178**	**4,730,623**	**16%**	**41%**

If access was defined purely based on grid connection, the use of lighting sourced from the grid shows it would have increased from 16% of the population in 2006 to 41% in 2016. However, if all electricity operated lighting technologies are considered, access in Kenya could be as high as 60% in 2016. About one in every six Kenyan households report using solar energy as their main source of lighting. While grid access multiplied by four over the analyzed decade, solar energy access for lighting increased over 12 times.

The dynamics of lighting choices should be unpacked further to understand them. Figure 4.2 reports the 2016 KHBS primary source of lighting reported by households, split by income quintile, rural/urban divide, and whether the household declared having access to grid electricity. As would be expected, urban areas with access to grid electricity almost exclusively use the grid as their source of lighting. However, in rural areas almost 25% of the two lowest income households that are connected to electricity declare using solar power as their main source of lighting. This could be explained by issues of reliability or affordability of the grid power, which renders light bulbs useless if power is not available in the evenings or if the bill is just too expensive. While there is no available widespread data on reliability, I have explored affordability issues earlier in this chapter.

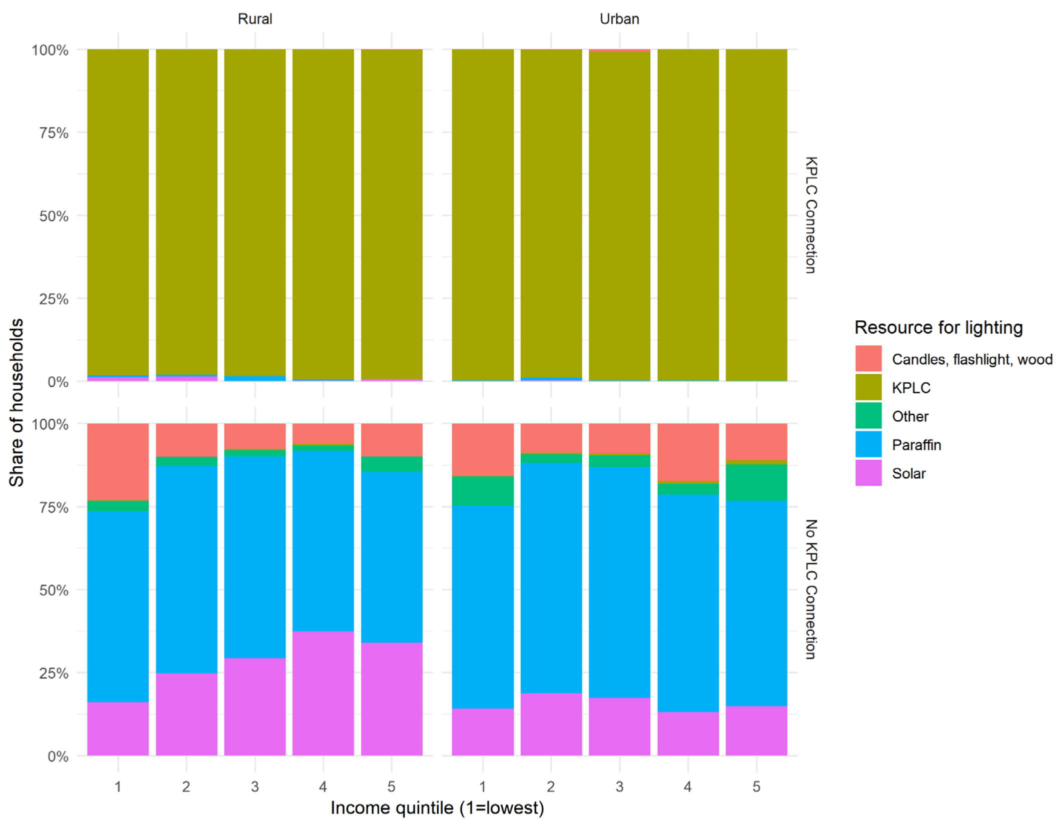

Figure 4.2 Share of population using a primary lighting source by income, rurality, and access to electricity for the 2016 KHBS

Households that declare no access to grid electricity report substantially different lighting choices. First, the use of paraffin is prevalent and slightly decreases with income. About 60%-65% of households in rural and urban areas declare paraffin as their main source of lighting, regardless of income. The fact that paraffin lamp usage does not behave as an inferior good may be related to the unavailability of other resources that provide similar performance. Solar lighting could be one of those potential substitutes, especially considering its negligible operational cost and indoor air quality benefits (Lam et al., 2017; Muyanja et al., 2017). The correlation of uptake of solar lighting in rural areas with income is consistent with its main drawback compared to alternative sources: high upfront costs[14]. Only 15% of lower income households report using solar lighting, increasing to close to 30%-35% of households in the higher income quintiles. However, the uptake of solar lighting in urban areas is apparently not influenced by income: roughly 15% of households report using this resource across the income spectrum. It is possible that the built urban environment, especially multi-family buildings, makes solar lighting less applicable due to barriers to

[14] The response from the private sector has been to implement "pay-as-go" solar home systems that recover their upfront costs through a rate much like a utility would do.

efficient sun exposure for the panels. It is also possible that solar lighting companies are targeting rural areas and not urban areas. In urban areas, paraffin seems to be a preferred resource over solar lighting, perhaps a consequence of the easier access to the fuel in cities. Finally, about 10%-20% of households across the country with no access to electricity report using candles, firewood, or flashlights as their main lighting source. These resources behave as an inferior good, as their usage generally decreases with income.

The widening of options in primary sources of lighting in Kenya in the decade between 2006 and 2016 was remarkable. In the 2006 KHBS the primary source of lighting was clearly driven by access to electricity: if a household had a connection it was used for lighting; if a household did not have a connection it used paraffin (Figure C.2). A negligible number of households used other sources of lighting. Solar lighting was only relevant for wealthier rural households with no grid connection, and even then only 10% of households in the highest income quintile reported using this technology.

The adoption of solar lighting in rural areas varies across income quintiles, but is relatively contained in a range of 10%-30%. In contrast, the distribution of solar lighting adoption across the country fluctuates substantially ranging from 10% to 70% of households (Figure 4.3).

Over 50% of households in counties located primarily in Western Kenya report using solar lighting as their primary source in the 2016 KHBS[15]. In contrast, counties in Eastern and Northern Kenya report very low penetration of solar lighting as primary source in the order of 5%-15%. What may explain the marked differences in location of solar lighting owners using it as a primary source of lighting? The 2016 KHBS asked households to report the main reason why they are not connected to electricity. Fifty seven percent of households that use solar lighting report the connection fee is unaffordable to them, compared to 65% of households regardless of their main lighting source. In addition, 25% of households that use solar lighting report the transformer is too far, compared to 16% regardless of the main source. These differences suggest that affordability is still the main barrier to accessing electricity, but that households that use solar lighting are driven (or forced) to do so more by the physical constraints of being far from the grid than by financial reasons compared to the rest of the households. Consequently, private solar lighting providers such as Boxx and M-Kopa have established their operations in Western Kenya and contributed to the spatial differences reported.

[15] Since there is little to no solar lighting reported in the 2006 KHBS, the analysis of distribution of solar lighting is only cross-sectional based on the recent survey data.

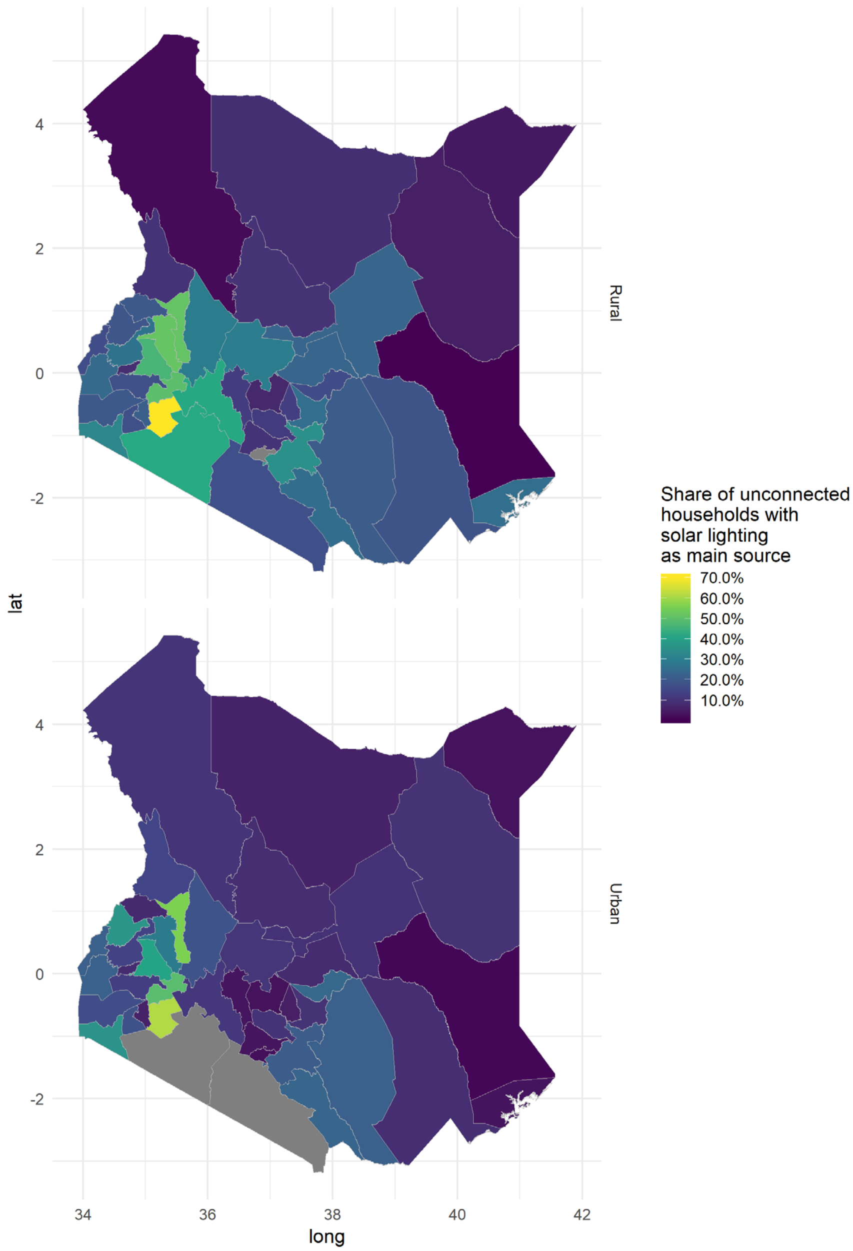

Figure 4.3 Share of households that report solar as their main source of lighting for households with no connection to the grid

This explanation is more plausible when analyzing the relationship between median county income and share of households by county that declare using solar lighting as their main source (Figure C.3). I have established that solar lighting ownership increases with income at the household level. However, when aggregating at the county level, the higher income counties in both rural and urban areas do not contain the highest share of households whose main source of lighting is solar. It is quite clear that solar lighting is concentrated in middle-income counties in rural areas

– with median household incomes of 36,000 to 60,000 KSh per annum. The share of households reporting solar lighting as their main source is below 20% in lower and higher income counties. This dynamic is more evident in urban areas. Since median household income at the county-level for urban areas is higher than for rural areas, solar lighting behaves as an inferior good: the share of households that declare solar lighting as their main source declines with income. This result highlights and support two conclusions:

- Solar lighting ownership is generally concentrated in middle-income counties, and within those in middle to high-income households.
- The geographical concentration of solar lighting most likely reflects a mix of reliability, availability, affordability, and access conditions that make two counties with similar median income have wide variation on the ownership of solar lighting as a main source.

In the analysis of lighting choices, the rural/urban divide and income levels are found to be important drivers of access. In the next section, I delve into the role that the rural/urban divide – particularly rural-urban migration – has played as a determinant for electricity access in Kenya.

C. Determinants of connection to grid-based electric supply

Despite the potential complexities in recording and interpreting information, the data in section 4.1.A shows an increase from ~1 million in 2006 to ~5 million in 2016 of households with electricity supply. Given population growth, households that report no electricity supply also increased from 5.5 to 6.5 million. However, the gains in access appear distributed unevenly across the population when these results are opened by income quintile and rural/urban divide (Figure 4.4). This figure shows the number of households that declare themselves as having access to electricity in the 2006 and 2016 KHBS, split by their weighted income quintile. The quintiles are calculated at the national level separately for each survey, which explains the large concentration of higher income household in urban areas and corresponding high concentration of lower income households in rural areas[16].

The data shows an increase of about a million rural low-income (first and second quintile) households without electricity from 2006 to 2016. In contrast, not connected urban households are generally stable, with minor increases in lower income quintiles and decreases in higher income quintiles over time. The vast majority of the increase in access from 2006 to 2016 occurred in urban middle and higher income households. There was a commendable increase in electricity-supplied rural households from 0.2 million to 1.1 million over the ten-year period, but this increase was also largely allocated to middle and high-income households.

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[16] The rural/urban classification was updated between the 2006 and 2016 KHBS. In particular, in the recent survey a new "peri-urban" category was defined. For comparative purposes, this new category was folded into the urban category.

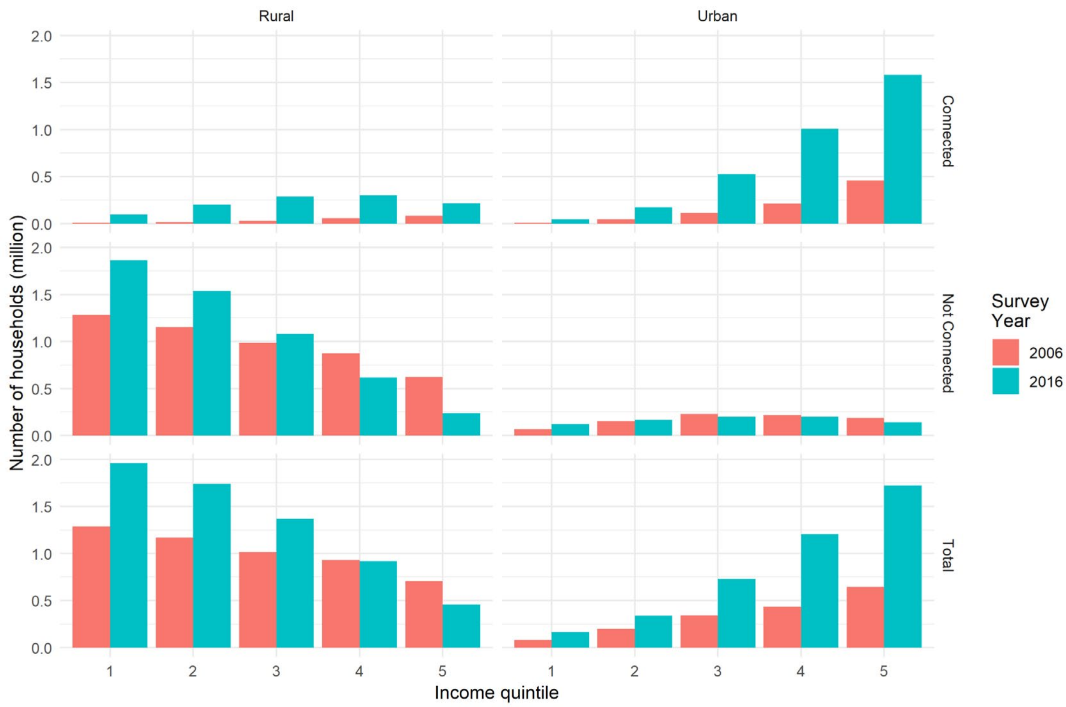

Figure 4.4 Number of connected, not connected, and total households in Kenya by income quintile and rurality

The change in the rural-urban population mix in Kenya was significant in the analyzed decade. In 2006, 76% of Kenyan households lived in rural areas, while in 2016 this figure had decreased to 56%. Between 2006 and 2016, over 3.2 million households appeared in urban areas, a rate of increase of almost three times the national growth in households in Kenya over the same period. This rate of increase shows that rural-urban migration may be dominating the growth of urban households in Kenya. When coupled with the access data, household migration suggests that the gains in access have not been due to the grid coming to the people, but the people coming to the grid. Middle and higher income rural households have migrated and gained access to electricity, while millions of poor rural households remain unsupplied.

The hypothesis that rural-urban migration has played a substantial role in electricity access, perhaps more than concerted efforts to expand the grid, should be studied in more detail. For this, I employ a Oaxaca-Blinder (O-B) decomposition approach to understand the drivers of electricity access increase across counties in Kenya. I develop the specification in equation 4.2 for percent change in electricity access:

$$\gamma = \alpha + \beta_1 \cdot \log(\rho) + \beta_2 \cdot \vartheta + \beta_1 \cdot \tau + \varepsilon \qquad (4.2)$$

where γ is the percent of population with access to electricity, ρ is the annual expenditure in real 2016 KSH, ϑ is the share of population living in urban areas, τ is a proxy for grid extension based on distribution transformer location and nightlights data, and ε is an error term. Specific comments on each variable, as follows:

- γ : I employ the percent of population with access to electricity clustered at the county level as the dependent variable. This is the minimum unit of analysis that can be used to create a repeated cross section.

- ρ : expenditure is a better descriptor of purchasing power than reported income (Wolfram et al., 2012). Expenditure is averaged across the county to identify how much income growth correlates with increases in electricity access. The 2006 cohort expenditure is adjusted to 2016 KSh using the consumer price index reported by the Kenya Central Bank (CBK, 2019).

- τ : the spatial extent of the grid is measured in two ways: (i) using raster data for Kenya and counting the number of 5 km^2 grids on each county that have a probability of 0.25 or higher to have access to electricity and (ii) counts of rural distribution transformers by county. Then, τ is a proxy for grid extensions[17].

- ϑ : represents share of population living in urban areas, which I use as a proxy for rural-urban migration. Unfortunately, the data does not allow separating changes in urban population stemming from net fertility or migration. Neither can I measure the actual flows of population from rural to urban areas.

I tested regressions using the two possible grid extension variables: the nightlights and the transformer counts. The nightlight data appear to be non-statistically significant for both cohorts, perhaps due to its coarse resolution or due to the year mismatch for the last cohort. I decide to drop this variable from the Oaxaca-Blinder decomposition and use rural transformer counts as a proxy for grid extension.

The O-B decomposition is implemented by assigning 2016 to cohort A and 2006 to cohort B. There are 47 counties with complete data in cohort A, and 45 in cohort B. The mean electrification rate is 0.298 for cohort A and 0.094 for cohort B, respectively. The mean difference in electrification rates to be explained with the O-B decomposition is then 0.204. The electrification rates in both cohorts are lower than reported earlier because the mean of electrification rates across counties is unweighted. Since the O-B decomposition is focused on explaining the mean differential across cohorts, weights would not significantly affect results.

Table 4.5 summarizes the regression results for cohorts A and B. Expenditure, as a proxy for income, has the expected sign in both cohorts: increases in average county-level income correlates with higher electricity access. This can be explained by several factors, most importantly the capacity of a household to afford the internal wiring and connection fee. The change in the coefficient over time, which grew almost four times between 2006 and 2016, may reflect the progressive lowering of the connection fee and overall connection costs that the REA and KPLC have implemented to reduce barriers to connection. The share of population living in urban areas also has an

[17] The nightlights variable could also be capturing densification. However, since nightlights will probably be visible already in places with some electricity access, intensification would only increase the probability of access as calculated in (Andrade-Pacheco et al., 2019). Given the low threshold, the difference in counts over time would reflect grid extensions (appearance of grids over a low threshold) rather than intensification (increase of the probability of access on a given grid).

expected positive sign, meaning that an increase in urban population correlates with higher electricity connection rates. The coefficient for this variable has increased approximately 25% over time, which could reflect densification efforts and reduced non-economic barriers to connection (the economic barriers should be captured in the expenditure variable). Finally, the variable that captures grid extension has the correct sign in both cohorts, but it is only statistically significant in the last cohort. The coefficient suggests that electrification grows approximately 1% every thousand transformers installed.

Table 4.5 Group A and B regression coefficients for Oaxaca-Blinder decomposition

	2006 KHBS (Group B)	2016 KHBS (Group A)
log(expenditure)	0.077***	0.256***
	(0.020)	(0.057)
Share of population living in urban areas (%)	0.424***	0.569***
	(0.049)	(0.069)
Grid extension (number of rural transformers)	8.41×10^{-5}	7.87×10^{-5}**
	(1.43×10^{-4})	(2.37×10^{-5})
Constant	-0.67***	-2.19***
	(0.182)	(0.480)
Number of observations	45	47
Adjusted R2	0.8448	0.8179

The O-B decomposition results are reported in Table 4.6 using two pooled regressions. The "indicator" regression uses the group indicator (i.e. the survey year) as a covariate. The literature has generally preferred to employ the no indicator method proposed by Neumark (1988). However, recall that the majority of the literature that employs the O-B decomposition is not comparing cohorts across time as this paper does. Then, the pooled indicator regression will capture year fixed-effects that could avoid attributing variation to any of the three variables of interest.

Table 4.6 Oaxaca-Blinder decomposition of rate of electricity access differences for two weighting methods

	Pooled, no indicator		Pooled, indicator	
	Explained	Unexplained	Explained	Unexplained
log(expenditure)	-7%	770%	-11%	774%
Share of population living in urban areas (%)	43%	10%	39%	15%
Grid extension (number of rural transformers)	49%	-22%	37%	-10%
Constant	0%	-744%	0%	-744%
Total share	86%	14%	23%	77%

Results of the O-B decomposition suggest that about 40%-45% of the variation in access to electricity across cohorts (i.e. over time) is due to changes in the share of population living in urban areas. Following the analyses earlier in this section, one interpretation for this finding is that about 45% of the gains in electrification have come from population moving to areas where the grid is already present. Grid extensions explain about 50% of the increase in electrification rates in the pooled O-B with no indicator, and about 40% in the pooled indicator. While grid extension explains a larger portion of the gains in electrification, it is only marginally larger than rural-urban migration and lower when including year fixed effects.

Expenditure or income explain very little of the gains in electrification, but have a substantial unexplained portion in both pooled models. This can be due to two reasons. First, real incomes appear to have declined over time in Kenya, especially in rural areas. The mean average real income in the 2006 KHBS is 9,214 KSh, whereas the same value for 2016 is 6,544 KSh. This is more evident when the survey vintage is used to produce the pooled coefficients (right hand side columns in Table 4.6). Second, recall that the unexplained portion is related to changes in the coefficients. As indicated, a large drop in the costs for grid connection sponsored by the REA and KPLC may have caused this structural change.

4.4 Discussion

This chapter has reported the progress in electrification in Kenya from 2006 to 2016 and uncovered several insights that may apply to electrification processes elsewhere.

First, measuring access to electricity is complex because there is not a clear definition of what "having access to electricity" means. In India, the definition of access to electricity was changing over time in the early 2000s as the electrification process unfolded and outcomes were verified. A preliminary definition of access would declare a village as electrified if an energized circuit within 100 meters from the village limits existed (Deshmukh et al., 2013). It became evident that this metric did not guarantee any improvements on the wellbeing of the inhabitants of an "electrified" village. This chapter has two insights related to defining access. The first is that asking whether a household has electricity or not in a survey is a very imprecise way of assessing the availability of electricity. The second is that access should ultimately be interpreted in a context where it improves livelihoods in some measurable way. A physical connection to a system may be insufficient if the grid is not available due to reliability issues, if consumers do not have access to appliances to transform electric power into useful end-uses, and if power is not affordable enough. In this chapter, I show how interpreting access as a tiered ladder can capture gradual improvements such as migrating some end-uses from low to high quality carriers. The dramatic increase in solar lighting in Kenya in the ten years analyzed in this chapter is an example of this. Most Kenyan households connected to the local utility consume less than 2 kWh per day, about 15 times less than households in wealthier economies. It is not clear then what end uses these households are meeting with high quality carriers, and which remain supplied with low quality carriers that could have detrimental side effects. However, when using an end-use based metric such as lighting it is at least reasonable to think that these households are not using paraffin, kerosene, or other sources with harmful indoor air quality consequences. These results support that efforts such as the World Bank's Multi-Tier Framework are headed in the right direction, but also highlight the wide gap in measuring and verification needed to accurately assess the impacts of electrification.

Second, the survey analysis revealed the relevant role that distributed resources – solar lighting and solar panels – are playing in enhancing access to electricity in Kenya. While solar panels are marginal contributors to electric supply across Kenya, this technology is the main (and in some cases, the only) source of electricity in rural areas of North and Northeastern counties such as Mandera, Turkana, and Lamu. Solar lighting is much more prevalent in Western counties in Kenya, where the majority of households in counties such as Bomet, Uasin Gishu, and Elgeyo-Marakwet use solar power as their main source of lighting. Impressively, all this progress in solar power development has been almost entirely provided by the private sector. The results from Chapter 3 show that distributed resources can play a substantial role to provide affordable, sustainable, and reliable electricity in urban and rural settings. The prevalence of solar lighting even in urban settings and across income quintiles provides empirical support to the results of the GAP model. There is enough evidence that developing policy frameworks that integrate and support distributed and centralized resources could boost electrification pace and outcomes in places like Kenya.

Third, electrification measurements and policies are generally focused on the national level and mask internal heterogeneity in the pace and levels of access. In this chapter, I leverage microdata information to report access to electricity supply and lighting by county, income quintile, and rural-urban areas. In Kenya, by 2016 over 80% of the upper quintile households across the country had access to electricity, contrasting to only 8% of the lower quintile households. This profound disparity is recognized through targeted connection and grid-extension policies. However, these results show that these policies are still falling short of providing universal access. The little progress made in electrification for lower income quintiles between 2006 and 2016 cast doubts on the capacity of the Kenyan government to effectively expand universal access to households in lower income quintiles by the target horizons. In contrast to the disparity in grid electricity access, about 25% of households in the lower income quintile and 80% in the upper quintile across the country have access to modern lighting – supplied by either solar panels or grid electricity. The higher equality of access to modern lighting compared to grid electricity further supports the relevance of including these technologies in broader and concerted electrification efforts.

Finally, the regression and decomposition analysis using the Oaxaca-Blinder decomposition provides insights on the relative contribution of different variables to the electrification process. In this chapter, I studied the relationship between income, share of urban population, and grid extensions to explain changes in the share of electrified households in Kenya. Results show that grid extensions and increases in urban population explain about 45%-50% each of the gains in electricity access in the 2006-2016 period. While imperfect, the variable used in the Oaxaca-Blinder decomposition should be capturing the effect of rural-urban migration on electricity access. The results suggest then that rather than the grid reaching to connect households, about half of the population that gained access did so because it came to the grid. The role of rural-urban migration and a quantitative measure of its impact on increasing access to electricity have not been available in the literature until now. These results prompt policy relevant tradeoffs. For example, it puts in perspective whether the large and expensive investments in grid extensions could have been better used to support rural-urban migration policies and development of urban infrastructure. It is possible that these policies would have produced larger long-term impact than grid extensions. This does not mean that rural grid-based electrification should be discouraged – it is still responsible for half of the gains in electricity access –, but that using other low-cost strategies that involve distributed resources could be a better use of capital when paired with active rural-urban migration policies.

Chapter 5

Conclusion

This dissertation has explored three different components of the challenge for emerging economies to achieve SDG #7. First, it presented a long-term capacity expansion analysis for the Kenyan power sector to assess the costs and benefits of transitioning into high renewable energy penetration futures. Second, it introduced the Grid Access and Planning model (GAP) – developed for this dissertation – to discuss how long-term capacity expansion is impacted by the inclusion of distributed resources in an integrated framework for electrification. Finally, it complemented these theoretical modeling results through the first empirical and longitudinal analysis of electrification in an emerging economy using microdata. In this conclusion section, I provide a summary of results and findings for each one of these components. Then, I connect these results with policy relevant applications related to design and implementation of electrification access strategies and distributed energy resource use in power systems. Finally, I suggest research avenues that stem from this dissertation, and propose a broader regulatory framework that should be developed to integrate current and future research results.

5.1 Summary of findings

I use the SWITCH capacity expansion model to explore low carbon development pathways for the Kenyan electricity generation and transmission sectors under a set of plausible scenarios for fast growing economies that include uncertainty in load projections, capital costs, operational performance, and technology and environmental policies. This research investigates the generation and transmission costs and operational and environmental impacts on the Kenyan expansion pathway of these variables and policies. I find that the Kenyan power system presents a unique transition from one basal renewable resource – hydropower – to another based on geothermal and wind power for ~90% of total capacity. I also find that a cost-effective and viable suite of solutions includes availability of storage, diesel engines, and transmission expansion to provide flexibility to enable up to 50% of wind power penetration. Results suggest that fast growing and emerging economies could benefit by incentivizing anticipated strategic transmission expansion. “Zero carbon emission” by 2030 pathways are possible with only moderate levelized cost increases of between \$3 to \$7/MWh with a number of social and reliability benefits.

Traditional capacity expansion modeling that focuses on large-scale generation and transmission does not evaluate the potential contribution of distributed resources – modular technologies that can be deployed close to load centers. To improve on these modeling limitations, I use a novel approach to assess the sequencing and pacing of centralized, distributed, and off-grid electrification strategies by developing and employing the Grid and Access Planning (GAP) model. GAP is a capacity expansion model to jointly assess operation and investment in utility-scale generation, transmission, distribution, and demand side resources. Contrary to the current practice, I find hybrid systems that pair grid connections with distributed energy resources (DER) are the preferred mode of electricity supply for greenfield expansion under conservative reductions in PV and energy storage prices. I also find that when distributed PV and storage are employed in power system expansion, there are savings of 15%-20% mostly in capital deferment and reduced diesel use. Results show that enhanced financing mechanisms for DER PV and storage could enable 50-60% of additional deployment and save 15 $/MWh in system costs. These results have important implications to reform current utility business models in developed power systems and to guide development of electrification strategies in underdeveloped grids.

A comprehensive development of electrification strategies requires complementing modeling results with empirical observations of the electrification process. I leverage two household budget surveys developed in Kenya in 2006 and 2016 as a unique data-driven window into the drivers of electricity access and the evolution of the electrification process. I find evidence that gains in electrification have come from grid extensions into rural areas as well as from people migrating from rural areas to cities, that rural grid extensions may be underutilized, and that poorer quintiles remain vastly unsupplied. Results highlight the role that modular technologies can play to complement traditional grid extensions to increase the pace and coverage of electrification efforts.

5.2 Policy applications

This dissertation provides several useful guidelines for policy-makers, developers, and funders that are designing, deploying, and financing electrification strategies and solutions in emerging economies.

First, it highlights the benefits that integrated planning processes and tools can bring to electrification strategies. Integrated resource planning (IRP) was developed in the U.S. in the 1970s in the wake of the oil crises and sought to integrated demand-side resources on an equal foot as supply-side resources on a least-cost analysis. Since the 1980s, it became evident that substantial energy efficiency and demand response could be tapped to serve load, which was not evident with traditional supply-side analysis. With the increase of variable renewable energy penetration in the early 1990s, models and processes in IRP began to adjust to analyze these resources more holistically, including their grid and environmental benefits, compared to other traditional resources. IRP enabled the adoption of energy efficiency, demand response, and utility-scale renewable resources by leveling the field and providing an assessment platform that integrated these resources into a decision-making paradigm. IRP is now grappling on how to incorporate DER into its framework, largely due to the historical division between the distribution and transmission-generation segments. This dissertation shows how the benefits of modeling these resources together, making visible sets of decisions that are not apparent with individual or scattered analyses.

Second, it shows that achieving higher and faster levels of electrification will require the orchestration of a number of entities, possibly by one or more governmental agencies. In wealthier economies, the final electrification push that brought universal access was carried in the earlier 20th century, and was spearheaded by governmental agencies largely using tax funding. Emerging economies will have to rely more on private capital than wealthier countries did, but the coordinating role of the state will remain essential. The empirical analysis of the Kenyan electrification process shows that rural-urban migration can be a powerful electrification strategy. However, no electrification frameworks include this concept as a tool that can be used to improve access to electricity. This same empirical analysis showed that adoption of distributed solar panels has increased dramatically, but that most of these belong to middle and higher income households with an electricity connection. The private sector can contribute to electrification, but needs clear guidelines and support to reach the most vulnerable and underserved population that has the greatest financial and logistic limitations.

Third, it shows the role that financing has in enabling electrification. Simulations of DER adoption with lower financing rates had a substantial impact in adoption of these resources. Again, the collaboration of financing institutions with governments and regulatory agencies can result in the development of targeted products for developers to bring down upfront costs or offer attractive financing packages for customers. On-bill financing has a track record of being a successful mechanism to fund demand side resources, and could be implemented by domestic utilities to channel finance to customers.

5.3 Future research

This dissertation leaves open several research avenues that are worth exploring. Chapter 2 suggested that diesel-based generation could play a relevant role in providing balancing and resource adequacy in nascent power systems before battery storage is adopted. However, the pollution impacts of diesel generation in urban settings, and how its costs compare to the benefits of using this technology remain unexplored. An integrated assessment model for electrification that includes damage functions as well as a representation of the power system could be one approach to address this open issue. In this same Chapter, we developed a relatively simple analysis of air conditioning adoption in Kenya. This analysis revealed that mid-day demand would increase significantly with air conditioning adoption, but that this increase would not shift the peak demand hours from the evening to the middle of the day. The air conditioning adoption analysis revealed that demand profile in emerging economies could suffer several structural changes stemming from the earlier and widespread adoption of plug loads such as phones and tables, electric vehicles, and battery storage, among others. Predicting the adoption of these appliances and devices is very difficult, but relevant to plan and design these future power systems, and more research is needed in this space. In parallel, techniques to plan under uncertainty in load levels and pace should be researched and adopted by policy makers in emerging economies that need to balance risk and cost in their electrification strategies.

The GAP model suggested that hybrid distribution systems that integrate and operate DER with power supplied from utility scale resources are the most common supply mode in greenfield settings. First, this result should be tested in mature systems that have substantial sunk costs in well-developed and designed distribution networks. Second, the grid systems that GAP suggests should be tested using a power simulation model for distribution networks that can include operational, safety equipment, and that tracks active and reactive power. I developed an interface to port GAP model networks to the OpenDSS platform and ran preliminary tests to explore this space, but substantial work remains. Third, the GAP model assumes that the entire system can be designed, invested, and operated by a centralized entity. While this applies to some jurisdictions, there are many regions where generation, transmission and distribution are not vertically integrated and their decisions are not jointly made. In addition, customers are typically who decide how much to invest in and how to operate DER following rate structures. An important line of research relates to the potential inefficiencies of this decentralized approach, which could be measured for the first time using the GAP model. Research underway at Lawrence Berkeley Lab using the GAP model is aiming to answer this question.

The empirical analysis of the electrification process in Kenya explored two related issues: the complexities of defining electricity access and the role that rural-urban migration might have had in increasing access to electricity. The different metrics explored for electricity access suggested that a policy-relevant metric should go beyond the connection to a supply system or the provision of a specific device such as a solar home system: it should be informed by the welfare improvements of electricity use. There is a nascent line of research that uses randomized controlled trials to test the impacts of electricity access on several welfare relevant outcomes. However, more research is needed to understand the impacts of electrification, to design electrification metrics based on these impacts, and then to develop and implement policies that use these metrics as targets. In terms of the rural-urban migration impact on electrification, there is essentially no research that studies this phenomenon. This dissertation has developed a simple analysis using Oaxaca-Blinder decomposition to disentangle how much of the gains in electrification come from the grid reaching people versus people reaching the grid, controlling by income gains. This analysis was performed over county aggregates, given data constraints, which restricts the validity of the results. Data that are more granular would improve the accuracy of the explanatory coefficients determined with the decomposition. As an alternative, a discrete-choice decomposition could be implemented instead of the current linear model using the same data. In the discrete choice implementation, the explanatory variable is whether there is a connection or not rather than the share of population with access clustered at the county level. This approach would increase the efficiency of estimators and improve on confidence on coefficients. Furthermore, the data used as a proxy for rural-urban migration in this analysis could be improved. The analysis used share of population living in urban settings, but it does not really track whether the increase is due to inflow from rural areas, migratory inflows from abroad, or changes in population due to birth and death rates. Improved modeling of these factors would help design targeted policies that embrace rural-urban migration as an effective electrification tool, or that at least accounts for this factor when determining the effectiveness of electrification programs more broadly.

Finally, most if not all of the policy suggestions from section 5.2 require changes in the existing regulatory framework that governs electricity provision in emerging economies. For example, integration of DER as an electrification strategy would require changes in rate structure and investment allowances for local utilities to be able to decide whether to provide electricity with grid power, distributed power on an off-grid mode, or both in a hybrid mode. The current framework discourages the deployment of DER by a utility because it cannot be readily recognized in a rate base. In doing this, it relies on the private sector to provide DER solutions, with the limitations of for-profit business models that make universal access challenging. The ways that utility regulatory frameworks are changing with DER adoption, higher renewable penetration futures, access to information, and extended grid automation have been studied extensively in mature power systems (e.g. Daniele, 2009; Deloitte, 2018; Glazer et al., 2017; Jairaj et al., 2016; MIT, 2016; PwC, 2014; World Economic Forum, 2017). However, the particular challenges and context of power systems in emerging economies make these recommendations and findings inapplicable, and even dangerous to implement considering the incompleteness and nascence of existing regulatory institutions. Recent work by Power for All (Power for All, 2019), WRI (Jairaj et al., 2016a) and MIT (Perez-Arriaga et al., 2019) have started to address this research gap. However, more targeted research at the country level will be needed to translate these general recommendations to local contexts, as well as additional work will be required to implement these insights. Ultimately, comprehensive electrification strategies will need to integrate technological advances, new modeling paradigms, and the domestic socio-cultural context into policy making to advance electricity access decisively in low-income economies.

Appendix A

A. The SWITCH Model

SWITCH is a deterministic linear programming algorithm that concurrently optimizes investment and operation of generation and transmission while meeting a detailed set of operational and policy constraints. Unlike many capacity expansion models for the electricity sector, SWITCH incorporates high spatial and temporal resolution for each region analyzed. In general terms, the model represents the transmission network by aggregating portions of transmission infrastructure that do not present persistent congestion. Each one of these portions is called a "load zone". Generation (centralized and distributed) and consumers are grouped in these load areas consistent with the topology of the simplified transmission system. For temporal representation, SWITCH-Kenya uses 2304 sample hours per simulation to match capacity and demand in each one of these hours, weighting the latter to represent energy needs for the whole horizon. Temporal synergies between demand and variable non-dispatchable supply are systemically captured through this novel approach.

The objective function for SWITCH is to minimize total system costs, as indicated analytically in equation A1.

$$System\ Cost = min\left\{\sum_{p,u} \rho_\rho \cdot \left(k_u \cdot I^{G,T}_{p,u} + F^{G,T}_{p,u}\right) + \sum_{h,u} \rho_{p(h)} \cdot \left(C^F_{h,u} + C^M_{h,u} + C^C_{h,u}\right) \cdot D^G_{h,u} \cdot w_h + \sum_{p,r}\left(k \cdot I^D_{p,r} + C^M_{p,r}\right)\right\} \tag{A1}$$

where $I^{G,T}{}_{p,u}$ are investment in generation G and transmission T in period p and for unit u; $F^{G,T}{}_{p,u}$ are their respective fixed costs; $C^F{}_{h,u}$ is fuel cost per operating hour h per unit u, $C^M{}_{h,u}$ are O&M costs, and $C^C{}_{h,u}$ are carbon costs, all multiplied by hourly dispatch $D^G{}_{h,u}$ and weighted by factor w_h; $I^D{}_{p,r}$ is investment in distribution in period p and load area r and $C^M{}_{p,r}$ its respective O&M costs. For efficient notation, a generation unit u is defined as a specific technology in a given location and a transmission unit u is an interconnection between two load areas. Investment costs are annualized through a capital recovery factor k_u and all costs are discounted to present using ρ_p. The discount rate is 7% in line with median Kenya Central Bank historical discount rates. We run sensitivities with lower and higher rates that made no impact in the decisions (see later in this Appendix).

The model enforces a set of constraints that make the simulation comply with basic power system restrictions, such as: maintain spinning and quickstart reserves, maintain minimum ecological flows from reservoirs, meet demand and supply at every single hour in the simulation, include the additional costs of ramping intermediate resources – usually natural gas plants – up and down to provide load following, respect transmission line capacity, and respect thermal, chemical, and mechanical storage stocks and capacity flows. The model also enforces existing policies, such as existing RPSs for states in the WECC and Chile and capacity additions for wind, solar, and nuclear for China. Numerical values for operational constraints are included in Table A.1.

The reduced linear program (LP) has between 4.8 and 5.5 million non-zeros and approximately 700 thousand equations depending on the scenario configuration. The LP is solved using the CPLEX solver and a barrier (interior point) optimization algorithm. Each iteration of the barrier algorithm takes on average 7 seconds and the entire simulation takes between 60 and 120 minutes depending on the scenario. The simulation is performed on a server with four Intel(R) Xeon(R) CPUs running at 3.33GHz and 32 GB of RAM.

B. Model inputs

Model inputs include:

- Daily profiles to represent hourly demand for different customer classes (Figure A.1)
- Load duration curve that shows the sampling mechanism for a given simulation period (Figure A.2). The sampling is such that both high and low demand hours are simulated to capture different demand conditions.
- Fuel prices (Figure A.3)
- Geothermal supply curve (Figure A.4)
- The three different load scenarios used for BAU and sensitivity runs (Figure A.5)
- Numerical values for different power system operational constraints, such as reserves, ramping, hydropower management, and storage management (Table A.1)

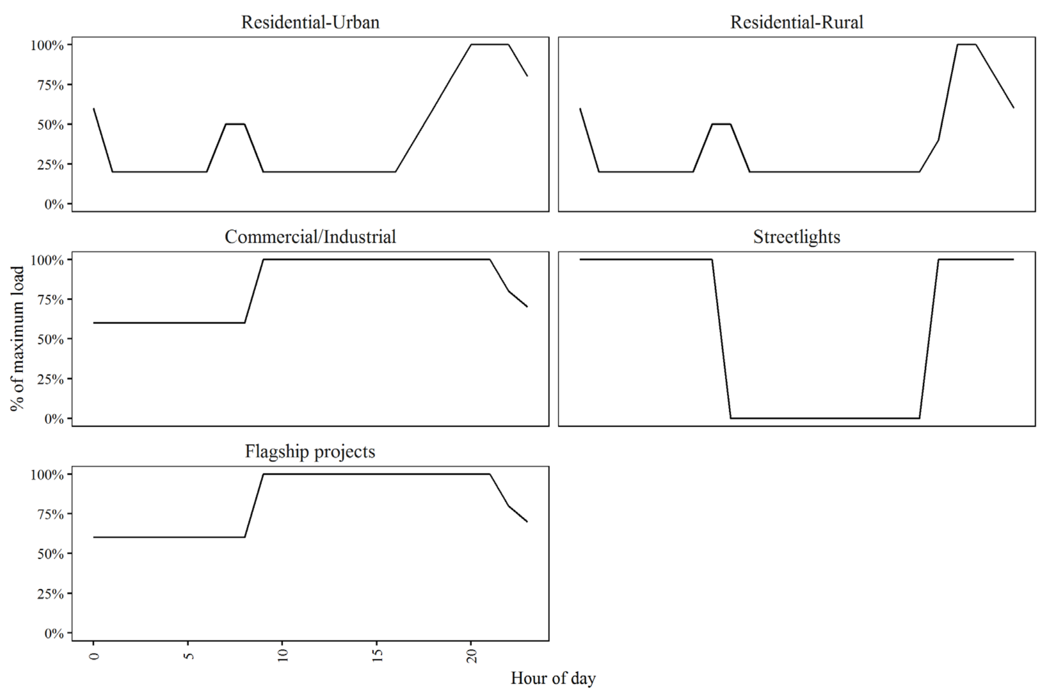

Figure A.1 Hourly profiles by customer class for a representative day of the year.
Profiles are expressed as % of maximum load to make them comparable.

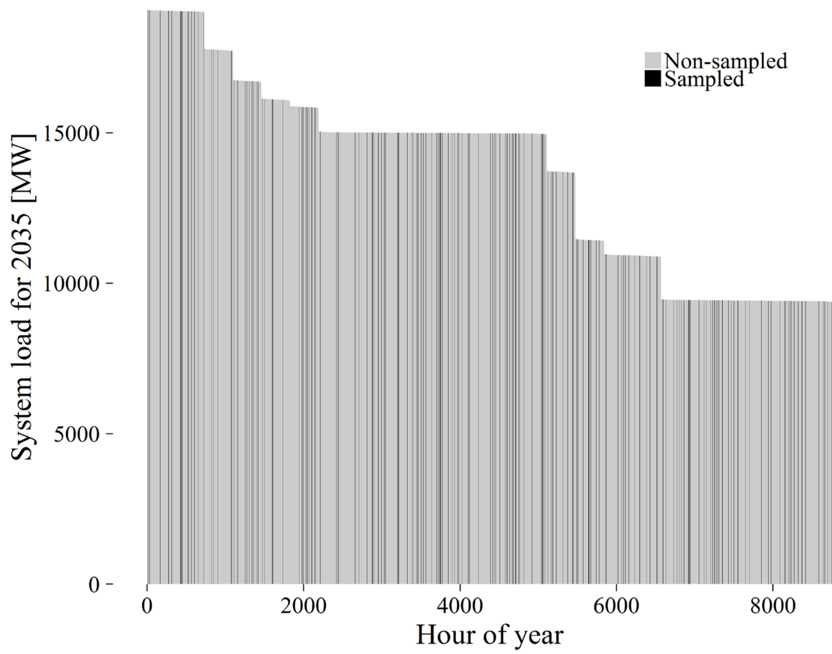

Figure A.2 Hourly load duration curve for year 2035 and the BAU scenario.
All load duration curves have the same shape, but their levels differ depending on the demand scenario and year.

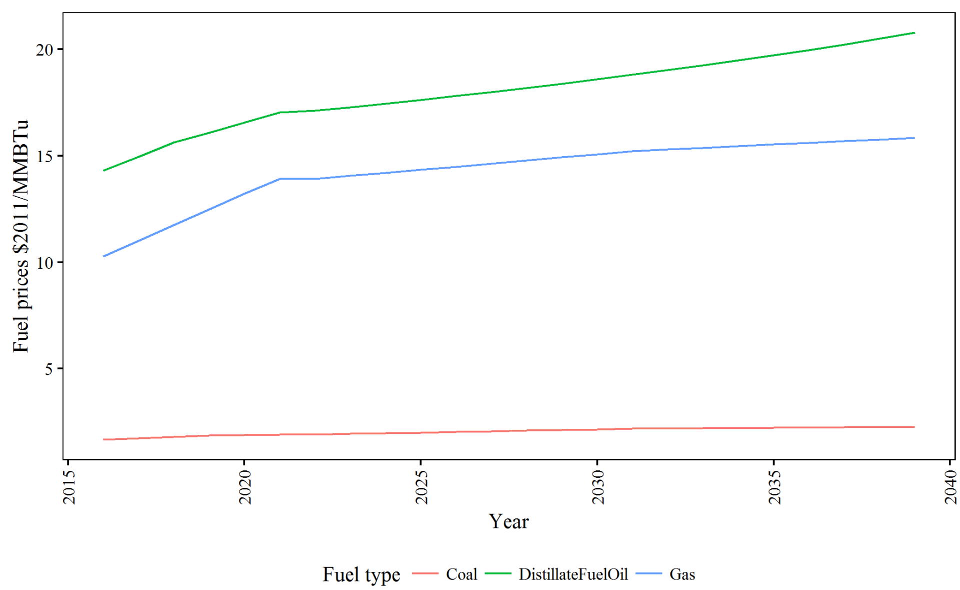

Figure A.3 Fuel prices for SWITCH-Kenya.

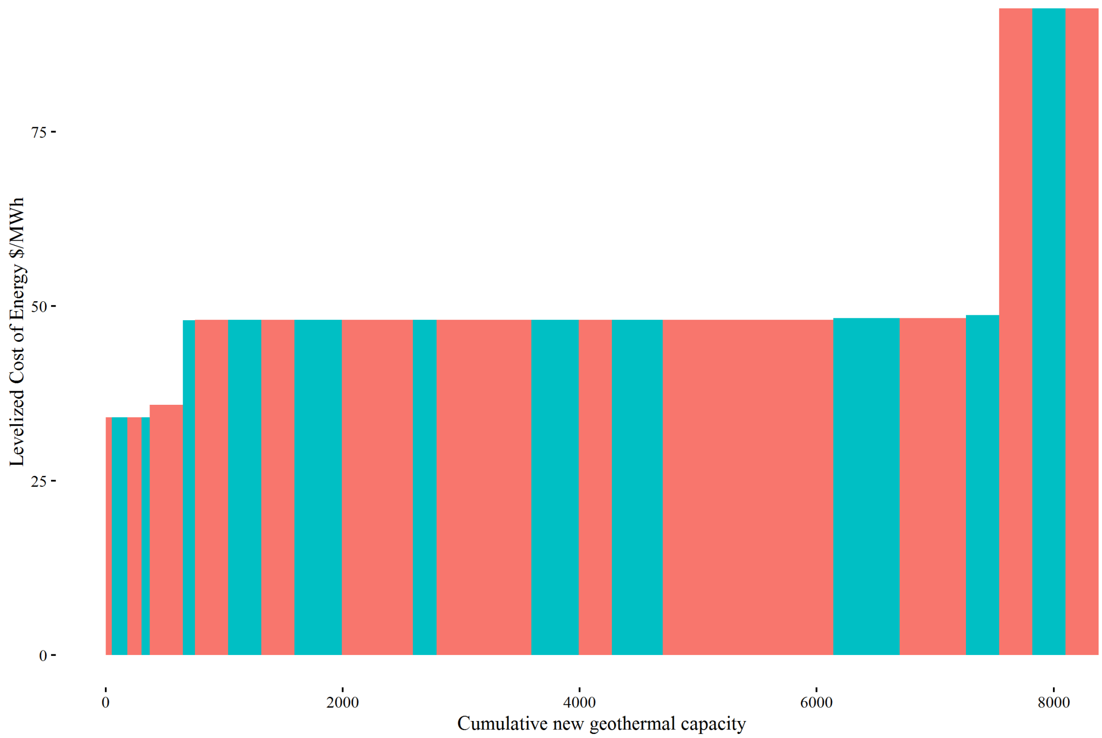

Figure A.4 Supply curve for geothermal energy.
Individual projects are identified arbitrarily as green or red for easier visualization. This curve shows how projects with different locations and operational conditions form a supply curve for geothermal resources, a much more realistic representation than a fixed unique cost.

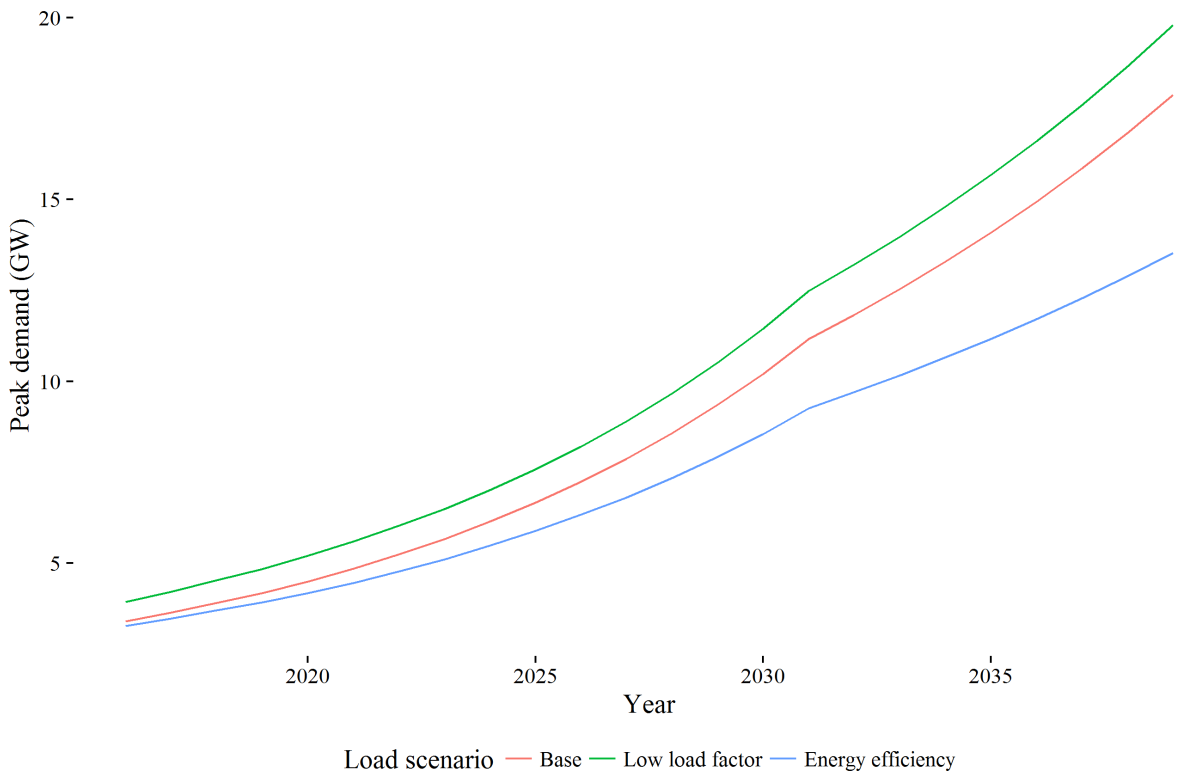

Figure A.5 Annual peak demand for the three load forecast scenarios.
The base and low load factor scenarios grow at an average of 8% a year. The energy efficiency scenario grows at an average of 5%. The low load factor scenario has peak demand of ~10% above the base case, but with the same energy consumption.

C. Comparison of SWITCH-Kenya results against existing modeling efforts in Kenya

A comparison of these results to the latest LCPDP update involves examining the planning process, the modeling tools used, and then the results obtained. The LCPDP process differs from our analysis in several ways. First, the LCPDP is akin to an implementation plan, while our analysis focuses on creating, simulating, and comparing many different scenarios. Second, the LCPDP generation and transmission expansion is studied as a sequence, while SWITCH allows us to concurrently examine both and explore possibly alternative expansion pathways. Finally, the LCPDP, as an implementation plan, is quite constrained, whereas our analysis explores pathways that may not be apparent to current stakeholders.

In terms of modeling tools, the LCPDP employs the WASP IV model (IAEA, 2001), which differs in many dimensions from the SWITCH model. WASP was developed to represent thermal systems with some hydropower presence, but has a poor capacity to properly represent variable renewable resources such as wind and solar. This is in part because the temporal representation in WASP is limited to 12 periods in a year, whereas with SWITCH we sample 24 full days for a total of 576 hours. This allows capturing synergies between load and renewable production that are otherwise missed. WASP is also a one-node model, while with SWITCH we simulate inter-county transmission interconnections to explore capacity and flexibility requirements. Finally, with

SWITCH we are able to simulate battery storage, which may become a central piece of future power systems in SSA. This technology is not available in WASP IV.

Results from the LCPDP process are consistent in some respects to our results, but also differ as a consequence of assumptions and constraints in the modeling process (see Table A.5). First, geothermal energy is the leading source of electricity in both analyses. Our results show 20% more geothermal power because we assume no nuclear energy is available. Second, presence of flexible turbines – gas and diesel operated – and absence of hydropower expansion are also common results in the two studies. Coal generation is uneconomical in SWITCH in almost all scenarios, but it is deployed in the LCPDP from 2025. Finally, wind power is the dominant variable renewable resource in both studies, but our results show double the capacity compared to the LCPDP by 2033. We also compare our results against the Renewable Energy Long Term Plan issued by the Ministry of Energy and Petroleum (Kenya MoEP, 2016). We generally find an agreement, as with the LCPDP, with geothermal and wind energy as the main sources of electricity for the long term.

D. Analysis of air conditioning adoption in the residential sector

The original residential consumption forecasts by KPLC do not seem to include air conditioning (hereinafter HVAC) adoption and use, since the load factor for this segment is unchanged through the forecast period. HVAC adoption should increase the load factor due to higher energy consumption without increasing the evening peak. Large penetration of HVAC could create a new midday peak demand. However, our analysis suggests this in unlikely to happen in Kenya within our timeframe.

To analyze the impact of HVAC use in hourly consumption profiles and overall capacity expansion of the Kenyan system, we develop a simple estimation of air conditioning adoption and use as follows:

1. Assumptions:
    a. We assume that HVAC will be adopted by urban residential customers only. This implicitly assumes the plausible case that KPLC forecasts include HVAC for the commercial sector and that there will be minimal adoption in rural areas given low income and credit constraints.
    b. For simplicity, we assume that HVAC is operated throughout the year, not only in warm months. This may overestimate HVAC energy consumption.
    c. We assume usage of HVAC proportionally doubles consumption of monthly residential level electricity and this proportion does not change in time. This is based on engineering estimations for monthly residential HVAC consumption in the order of 100-200 kWh (Muratori et al., 2012)
    d. Start year penetration of 0.5% is estimated based on reported assets in the 2005-2006 Kenya Household Budget Survey.
2. Method:

a. Define a typical hourly demand curve for urban residential customers that own HVAC. The residential hourly supply curve is based on HVAC use starting at 11 am and decreasing by 4 pm, following typical consumption curves in the U.S.
b. We estimate HVAC penetration based on the adoption curve derived in Letschert and McNeil (2010) (McNeil and Letschert, 2010), which provides a relationship between saturation and household income.
    i. Estimate average annual household income based on GDP per capita projections for Kenya at a 4.5% average annual growth rate and 4.4 people per household based on the 2009 Census.
    ii. This results in average annual household income growth from ~14 ThUSD in 2015 to ~31 ThUSD in 2035. The average household income we employ hides the high inequality in Kenya, which could result in an overestimation of actual saturation.
    iii. We linearize the portion of the S-curve in Letschert and McNeil (2010) that applies to Kenya for the ranges of household income mentioned before. This translates roughly to 0.25% percentage points of saturation increase per year.
    iv. As a result, HVAC saturation grows from 0.5% of urban households in 2012 to 7.5% in 2035.

3. Create a new aggregate residential hourly demand curve by blending the urban residential non-HVAC owner demand curve with the HVAC owner demand curve based on the proportional saturation share. For example, we estimate 2.5% of urban households in Kenya will own HVAC by 2020. Aggregate urban residential demand for each hour that year will be the weighted average of original non-HVAC demand (97.5%) and the new HVAC demand (2.5%). This is the input demand for the model when running this analysis.

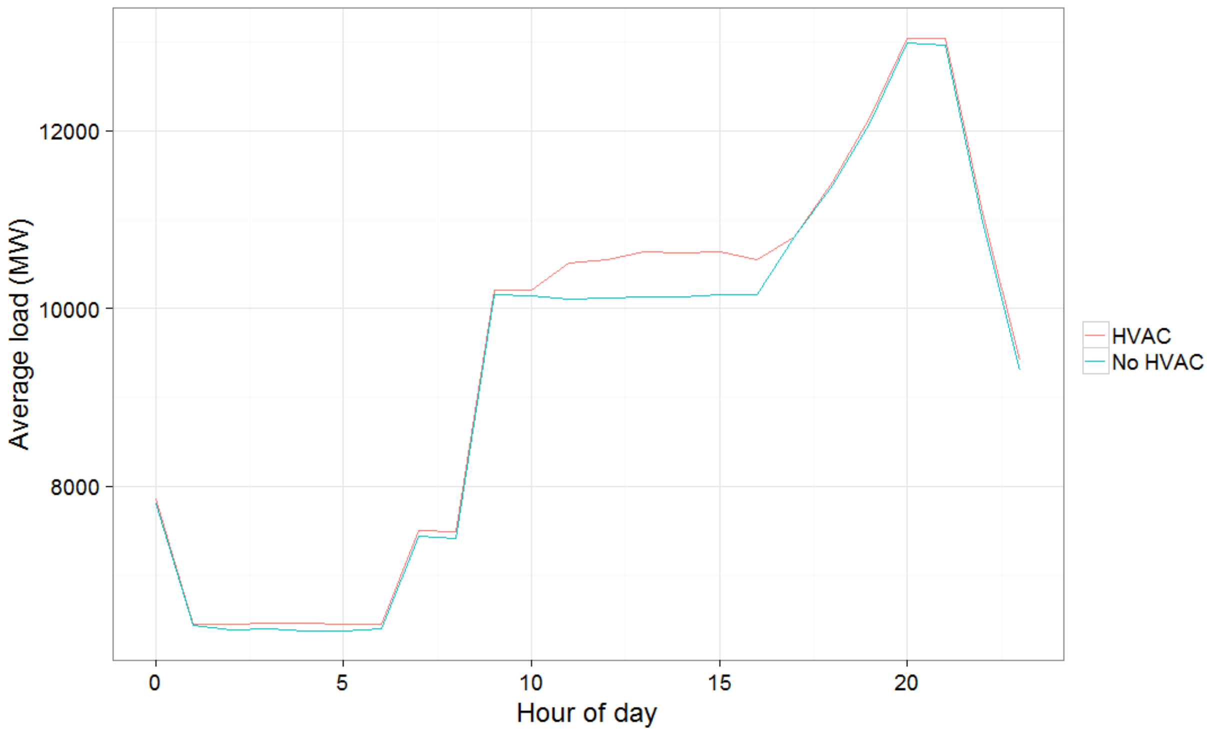

Figure A.6 Annual average hourly profile for system load with and without HVAC modeling for year 2035. HVAC adoption translates to about additional 500 MW in the middle of the day, but still is not enough to create a second system peak.

Under these assumptions, the impact of urban residential HVAC adoption on hourly load shape and energy consumption is not particularly significant (see Figure A.6). Two principal factors explain this. First, saturation of residential HVAC will be slow in a relatively poor country like Kenya when considering historical performance. Second, residential consumption is only 15%-20% of total consumption in the base KPLC energy forecasts we employ for this analysis. Residential load changes importantly with HVAC adoption and use, but this effect is diluted when aggregating load at the system level.

E. Discount rate sensitivity analysis

Discount rates are a measure to assess future cash outlays and make them comparable to present outlays. Higher discount rates translate to lower value for future expenditures, while lower discount rates make future expenditures closer to present.

A forward-looking capacity expansion model like SWITCH-Kenya uses discount rates to bring to present the expenses that happen in the future. This makes investments and operational expenses in different periods comparable to assess total system costs. The 7% discount rate we use is approximately the median historical central bank rate (CBR) reported by the Kenya Central Bank. There is no evidence that lower discount rates are applicable in a country like Kenya.

However, we still want to check if the investment decisions are sensitive to changes in discount rates. For this, we run two additional scenarios with a 3% and an 11% discount rate (±4% from the base case). The technology choice results are virtually unchanged. This is expected because the discount rates apply equally to all technologies and the time frame involved is not long enough to make more capital intensive technologies less economic than less capital intensive ones. System costs are different as expected, but a cost comparison is not meaningful in this setting because the discount rate is usually exogenous to the power system.

F. No-diesel expansion simulations

There is some evidence that when diesel generation is located near densely populated areas, it may have an impact on mortality and morbidity indexes for the nearby population. The SWITCH-Kenya model cannot properly account for the environmental impact of criteria air pollutants emitted by diesel generation. Assessing the environmental impacts of the generation units in any power system requires either an air quality and pollution dispersion model like Calpuff or Aermod or, at the very least, the application of marginal damage coefficients.

The development of an air quality module within SWITCH (or even in parallel) is beyond the scope of this modeling effort and would require a major architectural revision. Marginal damages – like the one used as a carbon tax – are technically possible to be included. However, there are no known studies for marginal emission damages (MED) of power plants in Kenya. MEDs are highly region dependent and are usually calculated for specific cities or areas within a country by modeling the emission source and a host of meteorological variables that affect pollutant dispersion. This makes very challenging to apply MEDs calculated for other regions or countries, as the MEDs vary substantially within the region or country.

Considering these limitations, we design several scenarios to assess the impact of not allowing diesel generation to be deployed. This restriction will produce alternative systems, whose cost and generation mix can be compared to the BAU scenario in order to determine the willingness to pay for no diesel deployment and the operational impacts on the power system.

We design three specific scenarios:

- No new diesel generation allowed (coded as NoDie)
- No new diesel generation, but 1 GW storage is available for deployment (coded as NoDie+Sto)
- No new diesel or coal generation allowed (coded as NoDieNoCoal)

Not including diesel plants in the BAU scenario yields less CO_2 emissions in 2020-2030, but three times more emissions in the last period (2035) due to the deployment of coal (Figure A.12). Comparing generation mixes, we find that these coal plants are deployed because there is not enough dispatchable capacity to meet peak demand (Figure A.15). This does lead to higher adoption of baseload (geothermal and later coal), but without the added flexibility this translates into much higher spilled energy.

The no-diesel scenario is on average 9-10 $/MWh more expensive than the BAU scenario that allows diesel plant capacity installation (Figure A.13). The main driver for this cost is additional baseload capacity and new transmission capacity required to mobilize that power to load centers.

Unlike most other resources in Kenya, diesel based generation has the advantage to be quite ubiquitous as it can be installed in any load zone.

Given that coal power plants are likely to pollute even more than diesel power plants, we run an additional scenario restricting deployment of both new diesel and coal plants. Compared to the pure no-diesel scenario, the gap left by coal is filled 50% by new geothermal capacity, 25% by wind and 25% by natural gas (Figure A.14). This scenario is slightly more expensive than the pure no-diesel one due to higher natural gas requirement, but still 10-11 \$/MWh more expensive on average than BAU.

The no-diesel scenario with Storage availability is very different. This scenario is more expensive (~2-4 \$/MWh) than the storage scenario that allows diesel. This is because storage in the no-diesel scenario is deployed earlier and in larger quantities, before it is fully cost-effective. However, the no-diesel storage scenario is still less expensive than the BAU scenario. We find that storage can effectively replace diesel capacity to provide flexibility. In the absence of diesel peakers, about 30%-35% additional storage capacity is installed in the no-diesel scenario compared to the regular Storage scenario. This additional capacity supports increased wind capacity and earlier geothermal deployment, as storage requires expanded capacity on other resources to charge and then discharge when needed.

We based this analysis on the idea that the cost differential between scenarios with and without diesel generation would suggest how economic a no-diesel scenario would be given the reduced emissions. We also explained how complex and delicate is to compare these results against MEDs obtained for other regions. For an approximate comparison, we extract the externality cost by technology determined by the European Environmental Agency in 2008 (EEA, 2008). The agency reports a low external cost for oil based generation of 70 €/MWh and a high cost of 220 €/MWh in 2005€. Adjusting for inflation and exchange rate, this corresponds to approximately 96 \$/MWh and 300 \$/MWh respectively, in 2015 dollars. These costs are about 8 to 20 times higher than the additional system expansion cost required in the no-diesel scenarios. It is still important to have in mind that Kenyan MEDs may very well be tens of times lower than European MEDs. However, this comparison suggests there are grounds for researching in more detail the impact of a no-diesel based expansion for the Kenyan power system.

G. Additional results figures

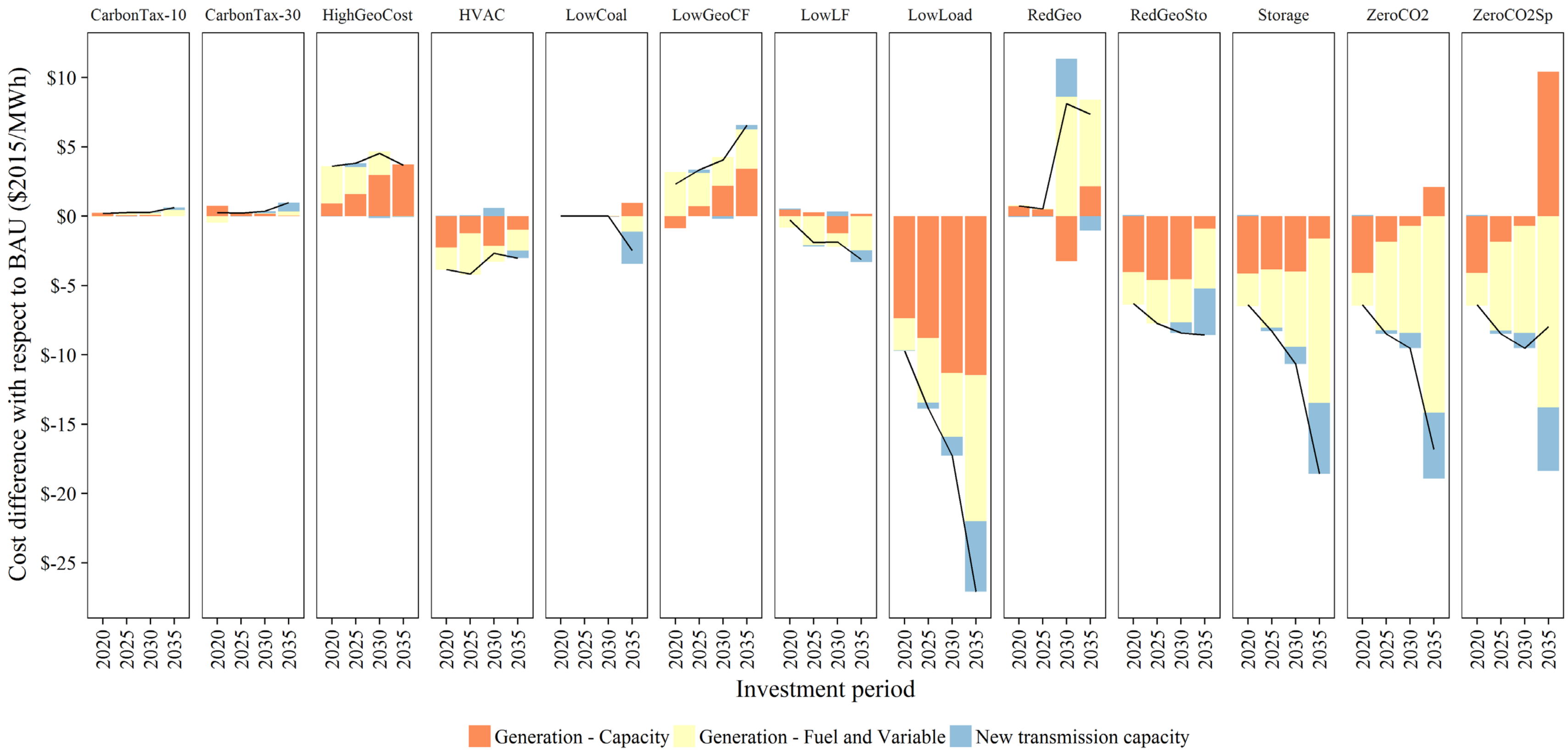

Figure A.7 Cost differences (in $2015) between BAU and each scenario, split by segment in the power system and period.

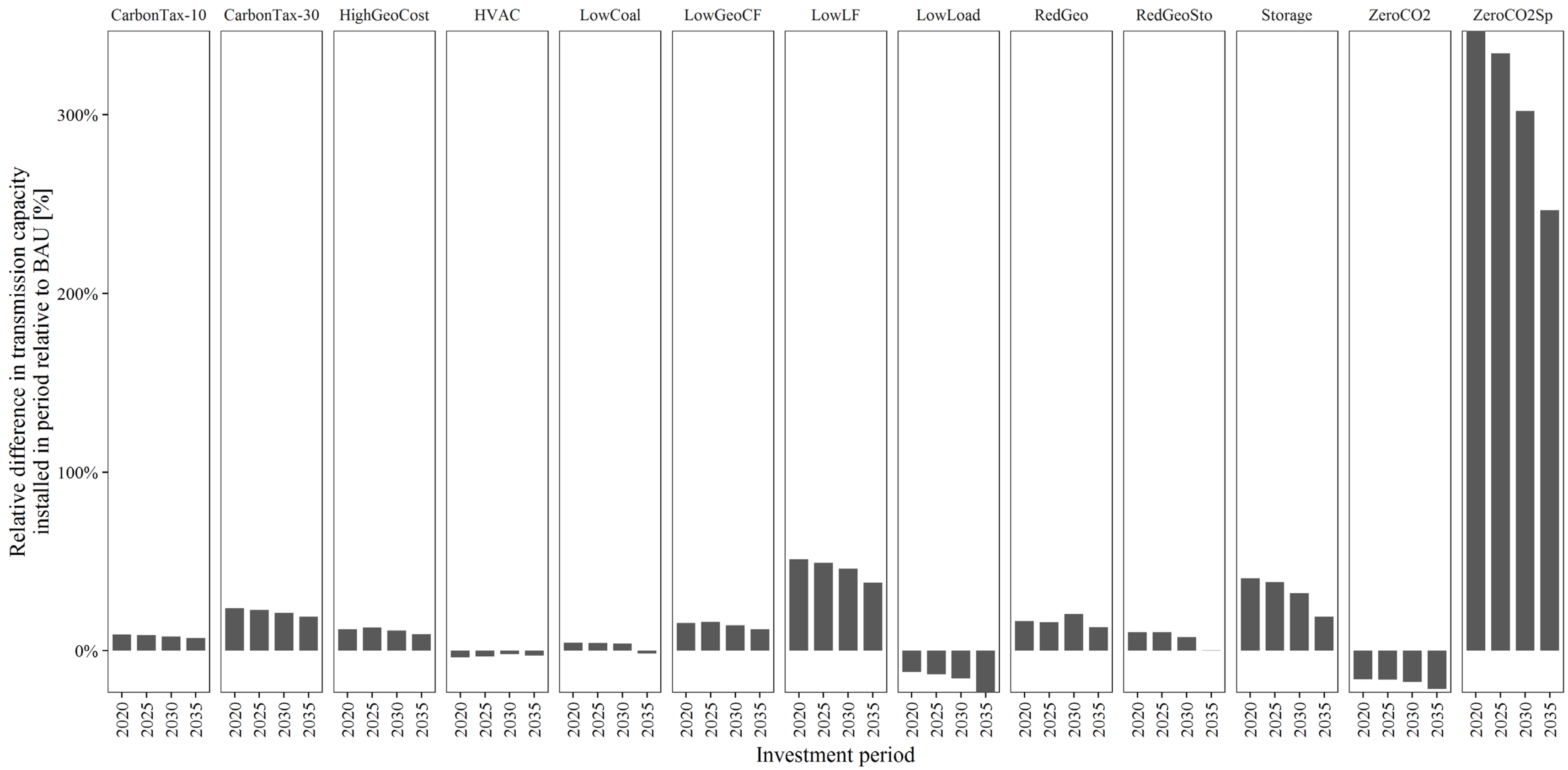

Figure A.8 Relative differences in cumulative transmission expansion capacity between each scenario and the BAU scenario per period, expressed in %. Transmission capacity is aggregated across all transmission lines in Kenya.

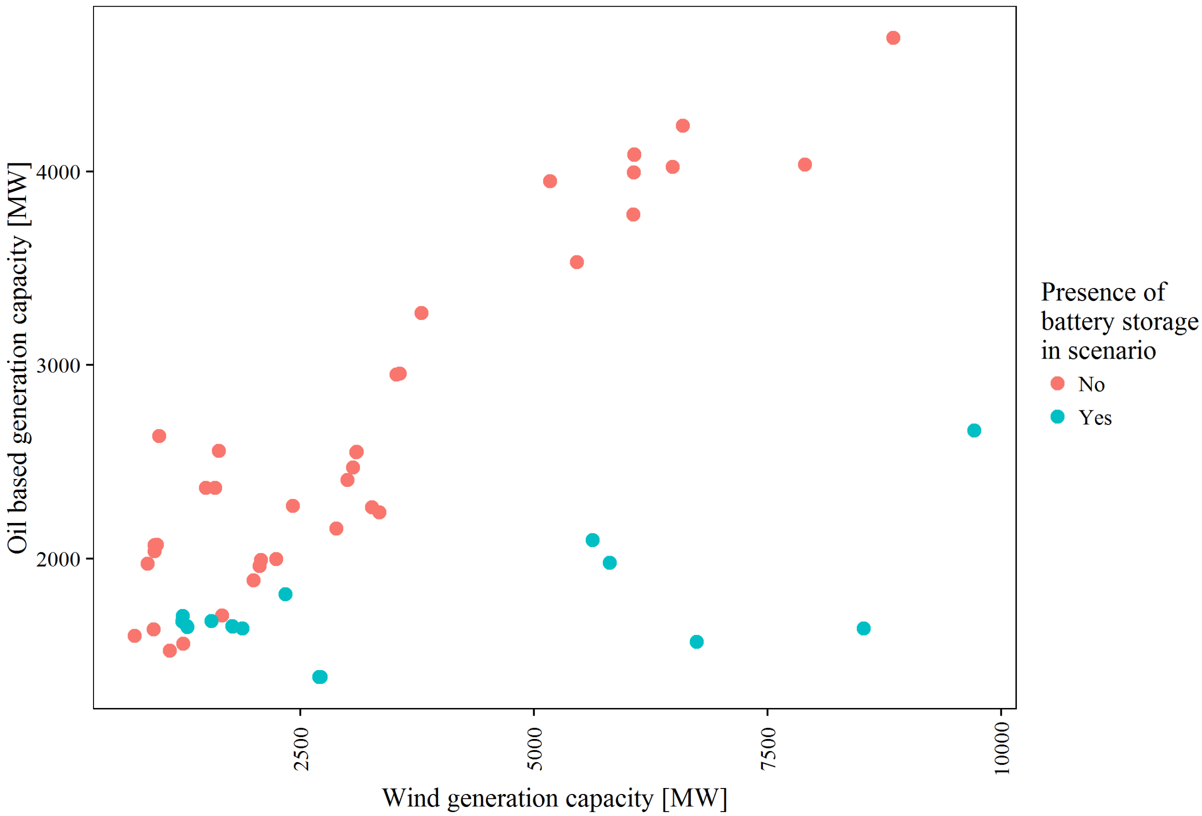

Figure A.9 Relationship between wind generation capacity and oil based (diesel/fuel oil) generation capacity for all scenarios.
Each point represents a period-scenario combination and we distinguish scenarios that include storage in the investment portfolio as it may act as a substitute for oil based generation.

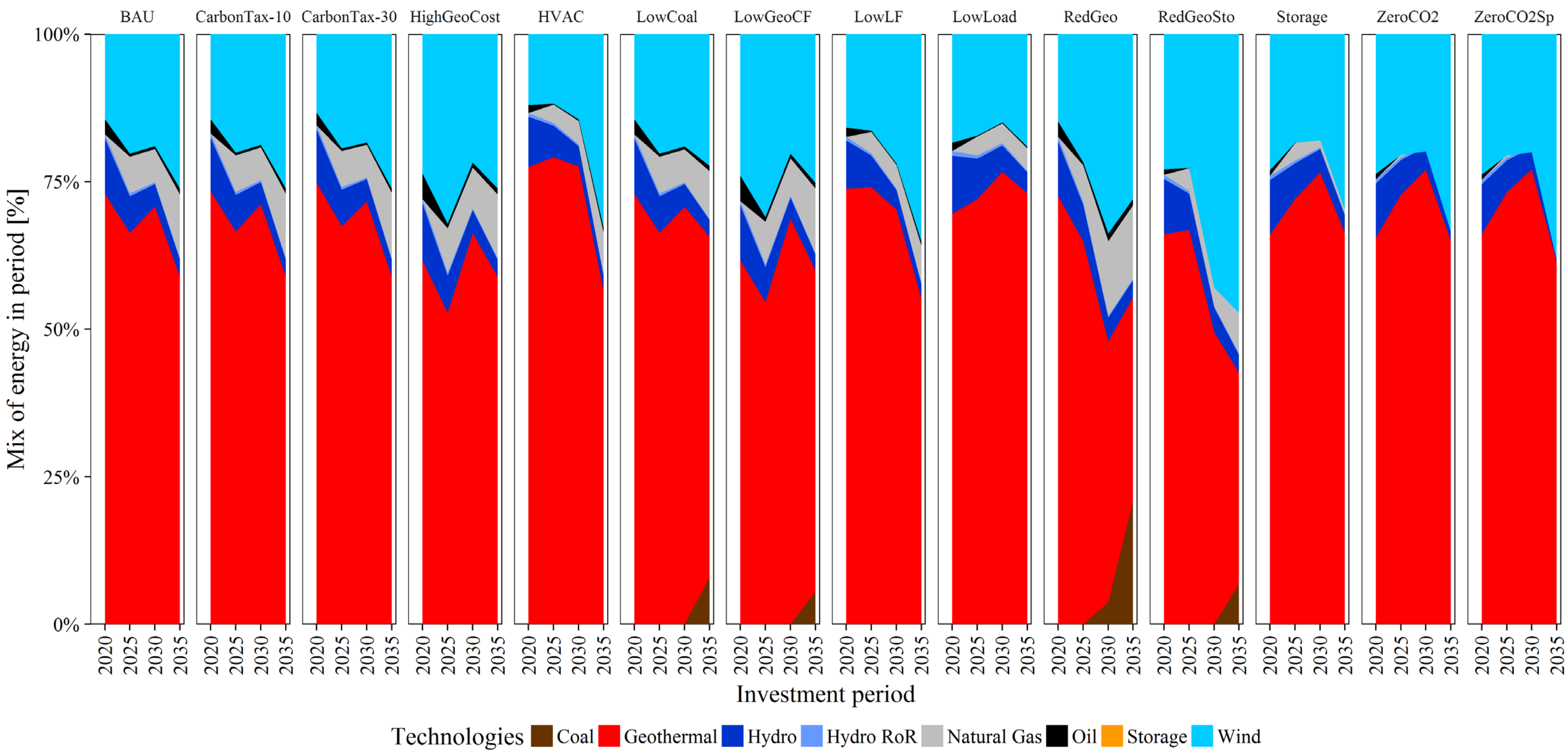

Figure A.10 Energy mix for each scenario, by period.
Storage efficiency losses are excluded from the figure as they are negligible compared to supply side production.

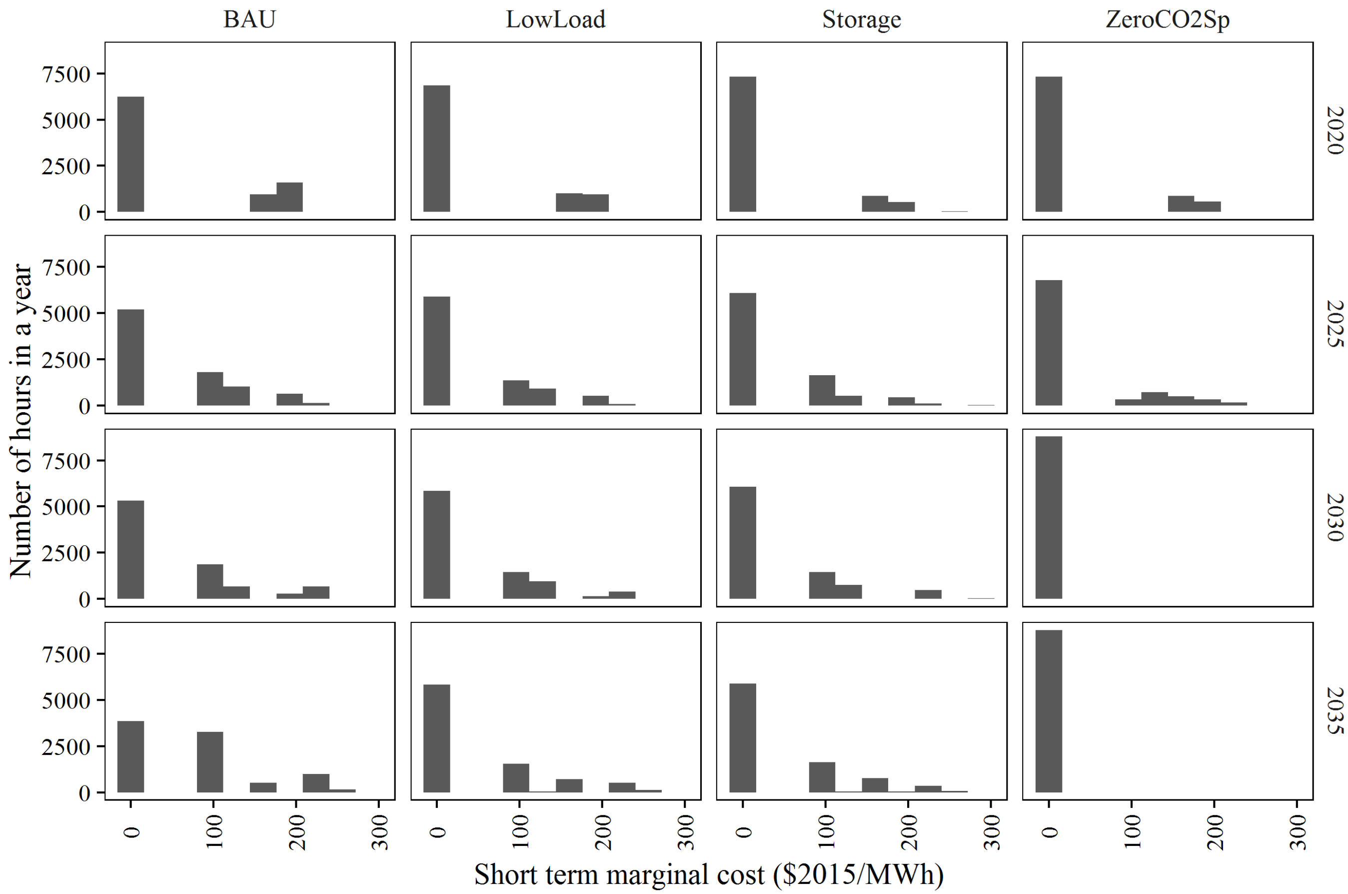

Figure A.11 Histogram of short-term marginal cost by period for selected scenarios.
Each period represents one year, so the total hours shown in each facet add up to 8760.

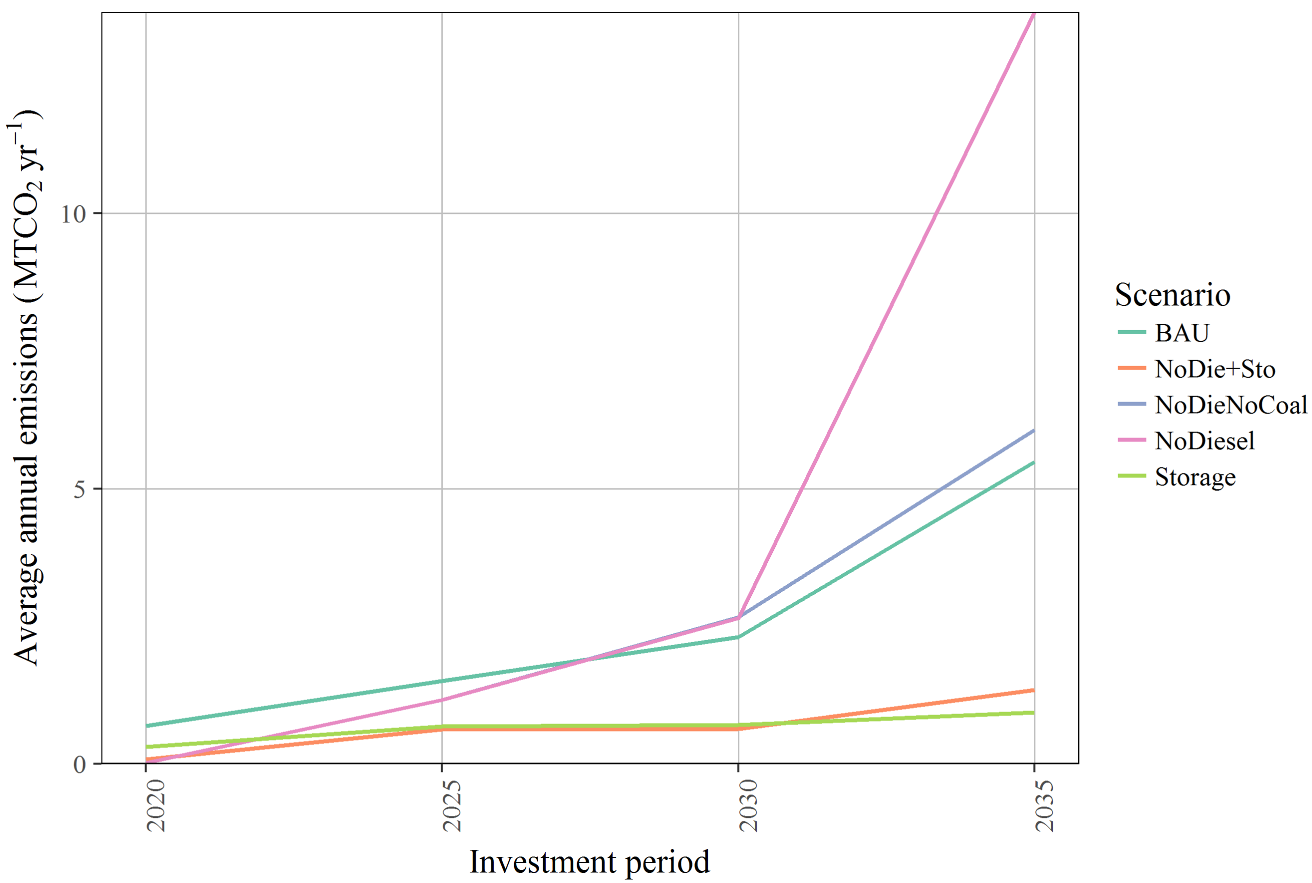

Figure A.12 Average annual CO2 emission profile for no-diesel scenarios

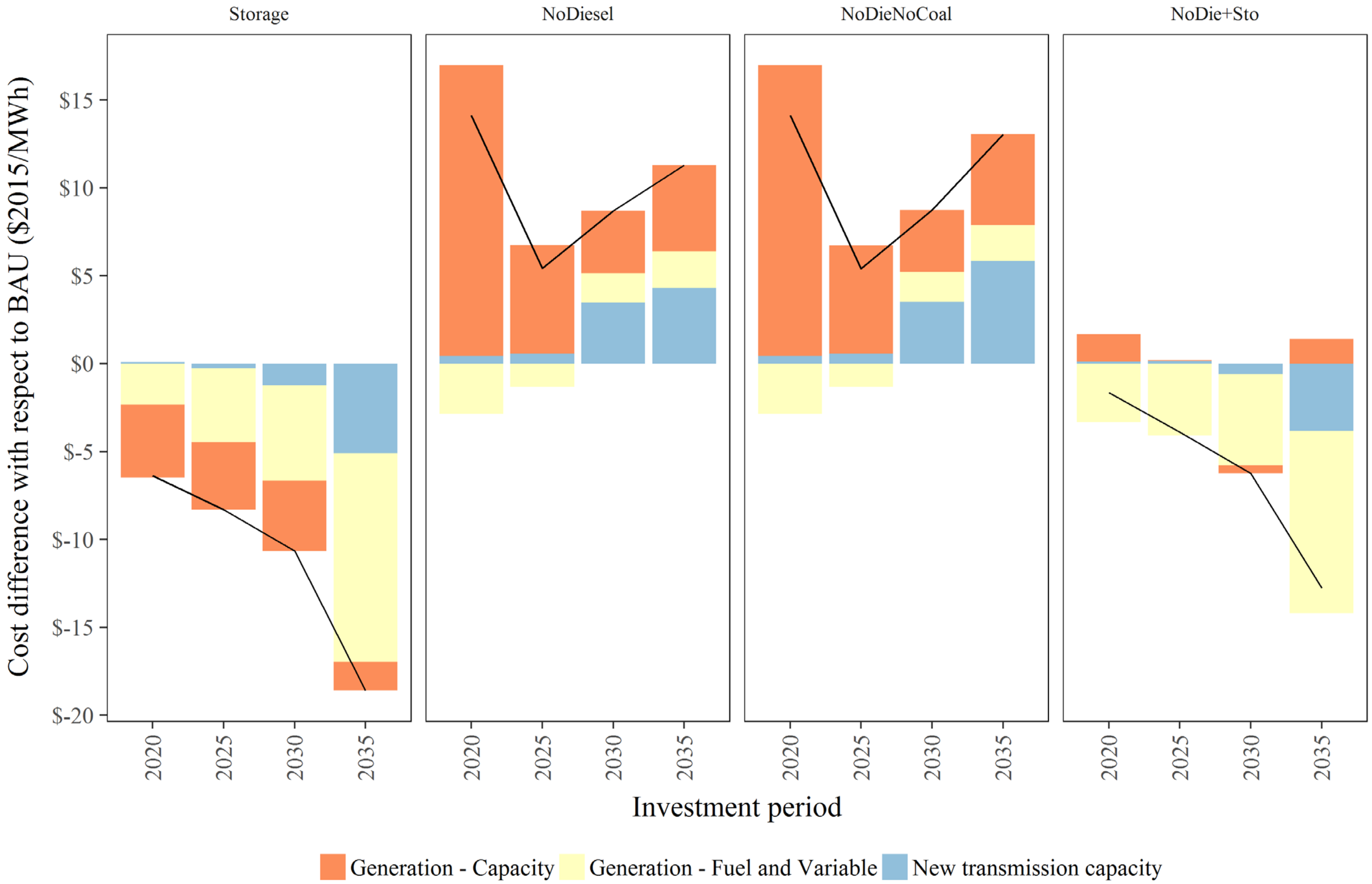

Figure A.13 Cost difference with respect to BAU scenario for no-diesel scenarios

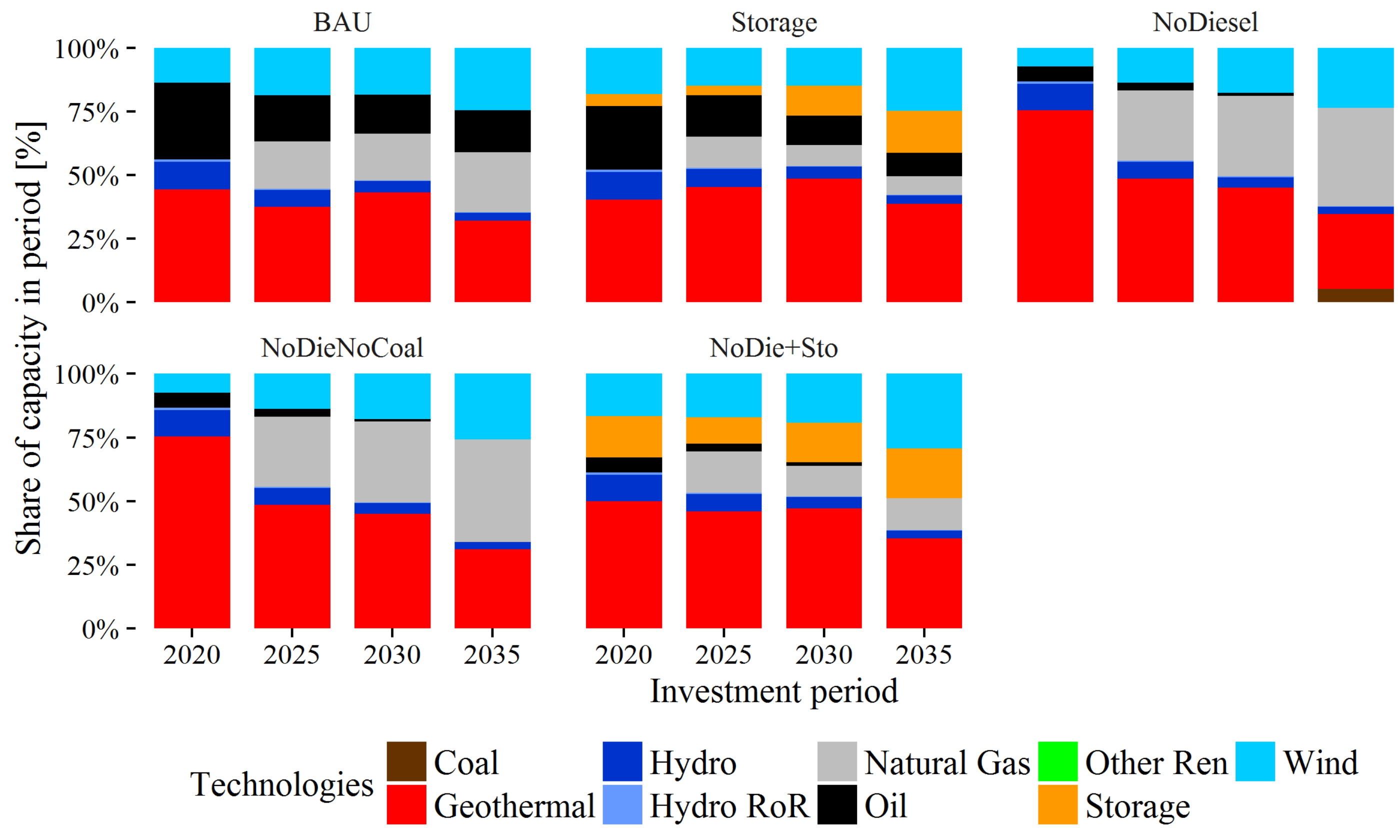

Figure A.14 Share of capacity by period and technology for no-diesel scenarios.

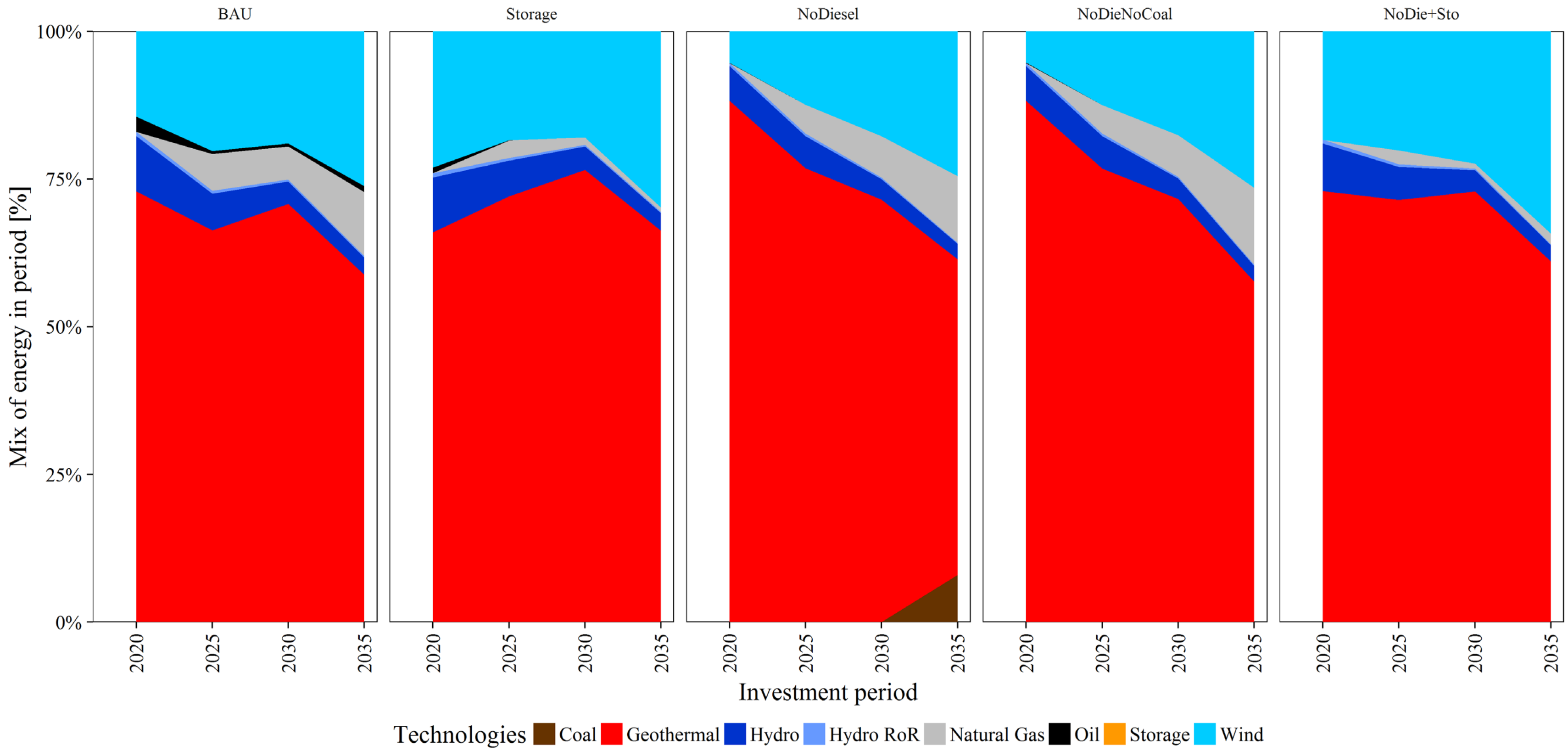

Figure A.15 Share of energy production by period and technology for no-diesel scenarios.

H. Additional result tables

Table A.1 Numerical values of operational constraints

Constraint	Value	Unit	Notes
Planning reserve margin	15%	of annual peak load	Additional capacity required for resource adequacy
Load only spinning reserve requirement	3%	of load	Traditional spinning reserve requirement for load following only
Wind-specific spinning reserve requirement	5%	of installed wind capacity	Additional spinning reserve proportional to wind deployment
Solar-specific spinning reserve requirement	5%	of installed solar PV capacity	Additional spinning reserve proportional to solar PV deployment
Spinning reserve ramping constraints: CCGT	25%	of installed capacity	Maximum available capacity to provide spinning reserve on a given unit. Corresponds to the 10-minute ramp rate
Spinning reserve ramping constraints: SCCT and engines	30%	of installed capacity	Maximum available capacity to provide spinning reserve on a given unit. Corresponds to the 10-minute ramp rate
Minimum storage requirement for spinning reserve	1	hour	Minimum hours of storage that need to be available for a given storage unit to provide spinning reserve
Heat rate spinning reserve penalty: CCGT	30%	of nominal heat rate	Additional heat rate penalty incurred by units of this type of technology when providing spinning reserve.
Heat rate spinning reserve penalty: SCCT ane engines	9%	of nominal heat rate	Additional heat rate penalty incurred by units of this type of technology when providing spinning reserve.
Quickstart reserve	3%	of load	Additional capacity required as operation reserve
Ramp up costs: CCGT	9.16	MMBTu/MW	Additional fuel cost for ramping a CCGT

Constraint	Value	Unit	Notes
Ramp up costs: SCCT and engines	0.22	MMBTu/MW	Additional fuel cost for ramping a gas or diesel turbine/engine
Minimum loading for baseload	100%	of installed capacity	Applies to geothermal, CCS, co-generation, and nuclear plants (if they exist)
Minimum loading for flexible baseload	40%	of installed capacity	Applies to coal steam turbines
Minimum flow for reservoir hydropower	50%	of available reservoir hydro capacity	Minimum dispatch requirement for reservoir hydro to mimic minimum downstream flow requirements
Hydropower operating reserve limit	20%	of available reservoir hydro capacity	Limits to 20% how much hydropwer capacity is available to be used as spinning reserve.
Storage discharge rate	100%	of installed capacity	How much of the installed capacity can be discharged on a given hour. Set at the same value as the installed capacity
Storage roundtrip efficiency	77%	of stored energy	Percentage of energy that is not available after being stored.

Table A.2 Investment, fixed, and variable non-fuel costs by technology.

Technology	Fixed cost /kW-yr	Variable non-fuel cost $/MWh	Investment cost Th$/MW (except battery energy storage, in $/kWh)			
			2020	2025	2030	2035
Battery Storage (capacity $/MW)	28	0.6	612	576	514	460
Battery Storage (energy $/kWh)	NA	NA	306	240	206	192
Bio Gas Internal Combustion Engine	124	0.0	2,579	2,579	2,579	2,579
CCGT (Combined Cycle Gas Turbine)	7.2	2.7	840	822	804	787
Coal Steam Turbine	29	4.2	3,246	3,246	3,246	3,246
DistillateFuelOil Combustion Turbine	18	4.2	489	489	489	489
DistillateFuelOil Internal Combustion Engine	18	4.2	489	489	489	489
Gas Combustion Turbine	16	3.7	556	556	556	556
Geothermal	48	3.4	1,964	1,893	1,825	1,759
Reservoir hydropower	13	0.0	1,959	1,959	1,959	1,959
Run-of-river hydropower	6.7	0.0	1,959	1,959	1,959	1,959
Solar PV	50	0.0	937	841	772	718
Wind	14	5.1	1,668	1,550	1,440	1,338

Table A.3 Total and per capita CO2 emissions and carbon intensity for selected scenarios.

Scenario	Period	Generated energy in period (MWh)	Period level emissions[1] (tCO_2/period)	Carbon intensity ($kgCO_2$/MWh)	CO2 emissions per capita (tCO_2/capita-yr)
BAU	2020	171,216,036	3,439,710	20.09	0.01
BAU	2025	257,563,126	7,536,767	29.26	0.03
BAU	2030	420,554,423	11,501,547	27.35	0.04
BAU	2035	555,757,912	27,441,018	49.38	0.08
LowLoad	2020	160,952,799	1,768,458	10.99	0.01
LowLoad	2025	231,924,091	3,456,638	14.90	0.01
LowLoad	2030	352,521,620	5,592,383	15.86	0.02
LowLoad	2035	459,296,430	8,780,103	19.12	0.02
HighGeoCost	2020	164,472,132	5,463,656	33.22	0.02
HighGeoCost	2025	254,809,793	9,307,733	36.53	0.03
HighGeoCost	2030	411,349,635	14,153,108	34.41	0.04
HighGeoCost	2035	555,736,036	27,402,987	49.31	0.08
LowGeoCF	2020	171,889,989	5,714,508	33.25	0.02
LowGeoCF	2025	270,191,747	9,488,453	35.12	0.03
LowGeoCF	2030	446,944,938	14,283,032	31.96	0.04
LowGeoCF	2035	601,067,084	57,833,406	96.22	0.16

Scenario	Period	Generated energy in period (MWh)	Period level emissions[1] (tCO_2/period)	Carbon intensity ($kgCO_2$/MWh)	CO2 emissions per capita (tCO_2/capita-yr)
Storage	2020	171,323,182	1,528,460	8.92	0.01
Storage	2025	266,505,977	3,424,081	12.85	0.01
Storage	2030	408,067,750	3,532,226	8.66	0.01
Storage	2035	545,509,069	4,655,645	8.53	0.01
ZeroCO2	2020	171,958,406	1,476,805	8.59	0.01
ZeroCO2	2025	271,979,451	1,333,903	4.90	0.00
ZeroCO2	2030	414,656,426	0	0.00	0.00
ZeroCO2	2035	556,106,254	0	0.00	0.00
RedGeo	2020	171,246,094	3,496,469	20.42	0.01
RedGeo	2025	257,732,716	7,577,430	29.40	0.03
RedGeo	2030	395,271,390	35,619,828	90.11	0.11
RedGeo	2035	549,388,103	128,091,884	233.15	0.35
HVAC	2020	188,947,649	1,972,771	10.44	0.01
HVAC	2025	296,452,076	4,269,917	14.40	0.01
HVAC	2030	469,434,752	9,236,756	19.68	0.03
HVAC	2035	640,914,964	23,231,630	36.25	0.06

[1]Period level emissions correspond to five years of cumulative carbon dioxide emissions.

Table A.4 Detailed scenario description

BAU Main Parameters			Scenario variations with respect to BAU					
Parameter Group	**Item**	**Value (all monetary values in $2015)**	**LowLF**	**LowLoad**	**HVAC**	**HighGeoCost**	**LowGeoCF**	**RedGeo**
Capital Costs	Solar PV	918 $/kW (2020) to 709 $/kW (2035)	No change	No change	No change	No change	No change	No change
	Wind	1669 $/kW (2020) to 1338 $/kW (2035)	No change	No change	No change	No change	No change	No change
	Storage (Ene)	306 $/kWh (2020) to 192 $/kWh (2035)	No storage	No storage	No storage	No storage	No storage	No storage
	Storage (Cap)	612 $/kW (2020) to 460 $/kW (2035)	No storage	No storage	No storage	No storage	No storage	No storage
	Diesel engines	490 $/kW (all periods)	No change	No change	No change	No change	No change	No change
	CCGT	841 $/kW (2020) to 787 $/kW (2035)	No change	No change	No change	No change	No change	No change
	Geothermal	2024 $/kW (2020) to 1812 $/kW (2035)	No change	No change	No change	2630 $/kW (2020) to 2355 $/kW (2035)	Reduced cap. Factor (85% instead of 94%)	Halved potential (4GW instead of 8GW)
	Coal	3246 $/kW (all periods)	No change	No change	No change	No change	No change	No change
	Transmission	1000 $/MW-km	No change	No change	No change	No change	No change	No change
Fuel Costs	Diesel	13.8 $/MMBTu (2015) to 19.7 $/MMBTu (2035)	No change	No change	No change	No change	No change	No change
	LNG	9.5 $/MMBTu (2015) to 15.5 $/MMBTu (2035)	No change	No change	No change	No change	No change	No change
	Coal	1.6 $/MMBTu (2015) to 2.2 $/MMBTu (2035)	No change	No change	No change	No change	No change	No change
Load	Energy	Average 8% annual growth	No change	5% average annual growth	~9% average annual growth	No change	No change	No change

BAU Main Parameters			Scenario variations with respect to BAU					
Parameter Group	**Item**	**Value (all monetary values in $2015)**	**LowLF**	**LowLoad**	**HVAC**	**HighGeoCost**	**LowGeoCF**	**RedGeo**
	Peak demand	Average 8% annual growth	10% larger peak demand	5% average annual growth	No change	No change	No change	No change
CO2 Intensity of fuels	Diesel	73 gCO2/MMBTu	No change	No change	No change	No change	No change	No change
	LNG	53 gCO2/MMBTu	No change	No change	No change	No change	No change	No change
	Coal	95 gCO2/MMBTu	No change	No change	No change	No change	No change	No change
Climate policy		None	No change	No change	No change	No change	No change	No change

BAU Main Parameters			Scenario variations with respect to BAU						
Parameter Group	**Item**	**Value (all monetary values in $2015)**	**RedGeoSto**	**Storage**	**LowCoal**	**CarbonTax-30**	**Carbon-Tax-10**	**ZeroCO2**	**ZeroCO2Sp**
Capital Costs	Solar PV	918 $/kW (2020) to 709 $/kW (2035)	No change	No change	No change	No change	No change	No change	No change
	Wind	1669 $/kW (2020) to 1338 $/kW (2035)	No change	No change	No change	No change	No change	No change	No change
	Storage (Ene)	306 $/kWh (2020) to 192 $/kWh (2035)	GWh decided by model	GWh decided by model	No storage	No storage	No storage	GWh decided by model	GWh decided by model
	Storage (Cap)	612 $/kW (2020) to 460 $/kW (2035)	1 GW max	1 GW max	No storage	No storage	No storage	1 GW max	1 GW max
	Diesel engines	490 $/kW (all periods)	No change	No change	No change	No change	No change	No change	No change
	CCGT	841 $/kW (2020) to 787 $/kW (2035)	No change	No change	No change	No change	No change	No change	No change

BAU Main Parameters			Scenario variations with respect to BAU						
Parameter Group	**Item**	**Value (all monetary values in \$2015)**	**RedGeoSto**	**Storage**	**LowCoal**	**CarbonTax-30**	**Carbon-Tax-10**	**ZeroCO2**	**ZeroCO2Sp**
	Geothermal	2024 \$/kW (2020) to 1812 \$/kW (2035)	Halved potential (4GW instead of 8GW)	No change	No change	No change	No change	No change	No change
	Coal	3246 \$/kW (all periods)	No change	No change	2435 \$/kW (all periods)	No change	No change	No change	No change
	Transmission	1000 \$/MW-km	No change	No change	No change	No change	No change	No change	No change
Fuel Costs	Diesel	13.8 \$/MMBTu (2015) to 19.7 \$/MMBTu (2035)	No change	No change	No change	No change	No change	No change	No change
	LNG	9.5 \$/MMBTu (2015) to 15.5 \$/MMBTu (2035)	No change	No change	No change	No change	No change	No change	No change
	Coal	1.6 \$/MMBTu (2015) to 2.2 \$/MMBTu (2035)	No change	No change	No change	No change	No change	No change	No change
Load	Energy	Average 8% annual growth	No change	No change	No change	No change	No change	No change	No change
	Peak demand	Average 8% annual growth	No change	No change	No change	No change	No change	No change	No change
CO_2 Intensity of fuels	Diesel	73 $gCO_2/MMBTu$	No change	No change	No change	No change	No change	No change	No change
	LNG	53 $gCO_2/MMBTu$	No change	No change	No change	No change	No change	No change	No change
	Coal	95 $gCO_2/MMBTu$	No change	No change	No change	No change	No change	No change	No change
Climate policy		None	No change	No change	No change	\$30/ton carbon tax	\$10/ton carbon tax	No emissions after 2035	No emissions after 2035

Table A.5 Comparison between SWITCH's BAU and ZeroCO$_2$ scenarios against the 2013 LCPDP results for the last year of simulation (in parentheses)

	Energy GWh			**Capacity MW**		
	LCPDP (2033)	SWITCH BAU (2035)	SWITCH ZeroCO2 (2035)	LCPDP (2033)	SWITCH BAU (2035)	SWITCH ZeroCO2 (2035)
Coal	19,493	0	0	5,400	0	0
Geothermal	60,066	65,387	72,293	7,264	7,953	8,793
Hydro	3,204	3,457	3,462	835	792	792
Natural Gas	2,098	12,108	0	3,960	5,860	178
Oil	31	1,067	0	410	4,087	1,569
Storage	N/A	N/A	21.3[1]	N/A	N/A	6,111
Wind	5,723	29,132	37,274	2,186	6,071	6,743
Nuclear	16,159	N/A	N/A	2,600	N/A	N/A
Imports	11,414	N/A	N/A	2,000	N/A	N/A
Total	118,188	111,152	113,029	24,655	24,762	24,186

[1]Denotes energy storage capacity in GWh, not production.

Appendix B

A. Details about the GAP model and additional results

This section describes the mathematical formulation of the GAP model objective function and its main constraints, alternative objective functions that are implemented and key parameters.

Mathematical model

p	investment period
h	sample hour
Z	set of load zones z
M	set of nodes m
G	set of generation units u
T	set of transmission lines n
D	set of distribution lines d
R	set of distributed resources r
$I^{G}_{p,u}$	installed capacity in generation unit u in period p
$I^{T}_{p,n}$	installed capacity in transmission corridor n in period p
$I^{D}_{p,d}$	installed capacity in distribution line d in period p
$I^{R}_{p,r,m}$	installed capacity in distributed resource r in node m and period p.
$K^{G,T,D,R}$	Capital cost for generation, transmission, distribution and DER technologies in \$/MW
$IS^{G,R}_{p}$	installed capacity in storage energy capacity in MWh for distributed resource r or unit u and period p.
$CX^{D}_{p,l}$	O&M costs.
$F_{p,u}$ $F_{p,n}$ $F_{p,d}$	Generation, transmission, and distribution fixed costs, respectively
$CF^{G}_{h,u}$	generation fuel cost per operating hour h, per unit u
$CX^{G,T,R}_{h,u}$	generation, transmission, and distributed resource O&M costs per operating hour h, per unit u
$CC^{G,R}_{h,u}$	carbon costs per operating hour h, per unit u
$X^{G,R}_{h}$	generation unit u or distributed resource r hourly dispatch
$L^{T,D}_{h}$	transmission line n or distribution line d hourly dispatched flow
$Si^{G,R}_{h}$, $Sa^{G,R}_{h}$	Charge (Si)/discharge (Sa) on hour h for utility scale or distributed storage decision
$Se^{G,R}_{h}$	Stored energy on hour h for utility scale or distributed storage
$J^{A,C}_{h,a,m}{}^{I}$	residential load from appliance a or commercial-industrial load, for node m and hour h
k_u, k_n, k_d, k_r	capital recovery factor for unit u, transmission line n, distribution line d, and distributed resource r, respectively
w_h	weighting factor for hour h
ρ_ρ	discount rate
σ_h	fraction of load to be met (proxy for ENS)
β_h	hourly reserve requirement
$\alpha_{u,n,d,r}$	forced outage rate for unit u, transmission line n, distribution line d, and distributed resource r, respectively
γ	maximum storage rate

Objective function

The objective function is the present value of the total system cost. In the same order as in the equation below, the costs components are investment in utility scale generation, investment in utility scale energy storage, investment in transmission capacity, investment in distribution network capacity, investment in DER, investment in distributed energy storage, fuel/O&M/carbon costs for utility scale generation, O&M costs for transmission, O&M costs for distribution, and fuel/O&M/carbon costs for distributed generation.

$$
\begin{aligned}
min\Bigg\{ & \sum_{p,u\in G}\rho_\rho\cdot\left((k_u\cdot I^G_{p,u}\cdot K^G_{p,u})+F^G_{p,u}\right)+\sum_{p,u\in G}\rho_\rho\cdot\left((k_u\cdot IS^G_{p,u}\cdot K^G_{p,u})\right)+\sum_{p,n\in T}\rho_\rho\cdot\left(\left(k_n\cdot I^T_{p,n}\cdot K^T_{p,n}\right)+F^T_{p,n}\right) \\
& +\sum_{p,d\in D}\rho_\rho\cdot\left((k_d\cdot I^D_{p,d}\cdot K^D_{p,d})+F^D_{p,d}\right)+\sum_{p,m\in M,r\in R}\rho_\rho\cdot\left((k_r\cdot I^R_{p,r,m}\cdot K^R_{p,r})+F^R_{p,r,m}\right) \\
& +\sum_{p,r\in R}\rho_\rho\cdot\left((k_r\cdot IS^R_{p,r,m}\cdot K^R_{p,r})\right)+\sum_{h,u\in G}\rho_\rho\cdot\left(CF^G_{h,u}+CX^G_{h,u}+CC^G_{h,u}\right)\cdot X^G_{h,u}\cdot w_h+\sum_{h,n\in T}\rho_\rho\cdot CX^T_{h,n}\cdot L^T_{h,n}\cdot w_h \\
& +\sum_{h,d\in D}\rho_\rho\cdot CX^D_{h,d}\cdot L^D_{h,d}\cdot w_h+\sum_{h,r\in R}\rho_\rho\cdot\left(CF^R_{h,r}+CX^R_{h,r}+CC^R_{h,r}\right)\cdot X^R_{h,r}\cdot w_h\Bigg\}
\end{aligned}
$$

Main constraints

(1) Satisfy load at the load zone level: on every hour and load zone, the sum of the power produced by utility scale generation, plus the incoming power from the transmission system, minus the outflowing power to the transmission system, plus the net storage decision, must equal the inflow into the distribution system through the transmission-distribution interface d_0

$$\sum_{u\in G} X^G_{h,u,z}+\sum_{ni\in T} L^T_{h,ni}-\sum_{no\in T} L^T_{h,no}+\sum_{u\in G} Sa^G_{h,u}-\sum_{u\in G} Si^G_{h,u}=\sum_{h,z\in Z} L^D_{h,d}\ \forall\ d=d_0$$

(2) Satisfy load at the node level: on every hour and node, the sum of the power produced by DER, plus the incoming power from the grid, minus the outflowing power to the grid must equal the fraction σ of load. In this paper σ = 1.

$$\sum_{r\in R} X^R_{h,r,m}+\sum_{di\in D} L^D_{h,di}-\sum_{do\in D} L^D_{h,do}+\sum_{r\in R} Sa^R_{h,m}-\sum_{r\in R} Si^R_{h,m}=\sum_{m\in M}\sigma_h\left(J^A_{h,a,m}+J^{CI}_{h,m}\right)\forall h,m\ \wedge\ 0\le\sigma\le 1$$

Constraint (1) applies at the reserve level as well, with the right hand side being the planning reserve margin and the left hand side restricted to technologies that can provide reserves. The hourly reserve requirement is β_h

(3) Dispatch of utility scale plants plus hourly reserve requirement β_h has to be less than or equal to the installed capacity on a given period, derated by the force outage rate

$$\sum_{u\in G} X^G_{h,u}+\ \beta_h\le(1-\alpha_u)\sum_{u\in G} I^G_{p,u}\ \forall h$$

(4) Dispatch of DER has to be less than or equal to the installed capacity on a given period, derated by the forced outage rate

$$\sum_{r\in R} X^D_{h,r}\le(1-\alpha_r)\sum_{r\in R} I^R_{p,r}\ \forall h$$

(5) Transmission flows cannot exceed available capacity derated by the forced outage rate

$$\sum_{n \in T} L^{T}_{h,n} \leq (1-\alpha_n) \sum\nolimits_{n \in T} I^{T}_{p,n} \, \forall h$$

(6) Distribution system flows cannot exceed available capacity derated by the forced outage rate

$$\sum_{d \in D} L^{D}_{h,d} \leq (1-\alpha_d) \sum\nolimits_{d \in D} I^{D}_{p,d} \, \forall h$$

(7) Storage logic. The following four equations constrain (i) the hourly storage to be below the maximum storage rate expressed as a ratio over derated discharge capacity, (ii) the release of stored energy to be below available stored energy on a given hour and existing installed discharge capacity on given period, (iii) total stored energy to be at most the existing installed energy storage capacity, and (iv) balance equation to track available stored energy from inflows, outflows, and efficiency losses. The equations are expressed for DER, but they are equivalent for utility scale storage implementation.

$$Si^{R}_{h} \leq \ (1-\alpha_r)\, I^{R}_{p} \gamma$$

$$Sa^{R}_{h} \leq \ I^{R}_{p};\ Sa^{R}_{h} \leq \ Se^{R}_{h}$$

$$Se^{R}_{h} \leq \ IS^{R}_{p}$$

$$Sa^{R}_{h} \cdot w_h \leq \ Se^{R}_{p} + Si^{R}_{h} \cdot w_h$$

Alternative objective functions

The model can be run as a cost minimization problem subject to utility or consumption constraints – such as minimum demand targets or meeting specific end-use services – or alternatively as a consumption maximization problem subject to budget constraints. Consumption can be a proxy for utility and welfare, particularly in the early stages of the energy ladder. GAP maximizes consumption rather than utility because there is little to no research on electric consumption utility functions. The main reason to employ a consumption maximization approach is that it represents better the reality of many low-income economies that have limited access to capital and wish to optimize the use of this capital to serve demand. The challenge with this approach, however, is to determine the appropriate levels of budget constraints. The cost minimization and consumption maximization approaches are fundamentally different in their calibration, applications, and outcomes. In this paper we choose to focus on the least cost problem; we leave a budget constrained analysis for a subsequent paper.

Losses parameter sensitivity (distribution system efficiency)

Distribution system losses are very high in SSA, reaching up to 50% in some cases (Kojima and Trimble, 2016). These reported losses are a mix of technical losses – due to poor construction and maintenance and low circuit capacity – and non-technical or commercial losses – due to poor metering, billing, and revenue collecting practices. To represent losses, the GAP model uses an efficiency parameter instead of resistive and reactive losses. This is because the model implements a transportation model instead of a power flow due to computational constraints. This efficiency parameter was set to 15% loss per 100 miles of distribution system line. This parameter represents technical losses as well as typical levels of non-technical losses that are part of distribution system commercial operation. We assume distributed resources do not accrue technical or non-technical losses and that both technical and non-technical losses increase linearly with consumption.

We calculate system losses as wire energy losses divided by consumption for a given region. Total system energy losses are about ~18% in the "traditional" expansion system. Losses are ~17% in 2020 and decrease to below 15% in 2030 for the system that allows PV and storage. These values are high for developed power systems but are consistent with actual values for SSA countries. Increased adoption of "lossless" distributed generation explains the decrease in losses in the distributed scenario. Losses do not vary significantly with the inclusion of modular PV and storage technologies in a given load zone, but do vary substantially across load zones (Fig. A8). High and medium density load zones do not have the longest grids but is where higher consumption customers are located. This translates to energy losses in excess of 25% for high density and 20% for medium density areas, respectively. This compares to 1%-2% losses in low density areas that have shorter grids. This is explained because we are calculating losses as proportion of zonal consumption. The share of demand that is supplied from lossless off-grid systems as opposed to the centralized grid is higher in sparse zones, which translates to smaller and shorter circuits. When we calculate losses as a percent of transmitted energy, we verify that this parameter does not differ across load zones, as expected.

We test three alternative parameters at 3%, 5%, and 10% losses per 100 miles of distribution line over the system that allows distributed PV and storage (Fig. A9). Total system losses drop to around 5%, 6-7%, and 11-12%, respectively, with these alternative parameters. We verify that the loss parameter does not impact utility-scale generation installation, but does impact distributed resource deployment. About 11 GW of distributed resources are installed by 2030 with the 3% parameter, increasing to over 15 GW with the original 15% parameter. This result is intuitive: as the grid is less efficient, larger deployment of distributed resources to meet demand at the node level becomes more cost-effective. On average there is ~300 MW of distributed resource capacity added for every 1% of additional system losses. It is relevant to note that even with a very low efficiency parameter there is significant installation of distributed resources, particularly storage.

Losses levels have an effect on the optimal supply mode decisions and the threshold distances for transitioning into different supply modes. Changes in loss efficiency parameter have little effect in supply mode decisions in dense areas where the vast majority of optimal supply modes include a mix of grid connection and distributed storage (Figure B.10). However, in medium and low density areas there is a halving of the number off-grid nodes when the efficiency parameter decreases from 15% to 3% losses per 100 miles. As the grid gets more efficient, it becomes optimal to switch previously unconnected nodes into hybrid modes. Accordingly, as grid efficiency increases the threshold distances for nodes to switch from grid connected to off-grid also increase (Figure B.11). In medium and low density areas, off-grid nodes are located at a median distance of 250 km with a 15% loss parameter, increasing to 320 km with a 3% loss parameter.

Impact of DRE in distribution system topology

We study how the size of the distribution system depends on the adoption of distributed resources. We measure the size of the distribution system by the length and capacity of its circuits. We find that the "traditional" expansion system with no distributed resources requires about double the circuit length compared to the grid with distributed PV and storage (Figure B.3), but only ~30% more capacity (Figure B.4). The length difference is explained by a 40-50% additional MV circuits installed in the traditional scenario. We find that distribution grids are more meshed in absence of distributed resources, particularly in dense areas with high demand. This may respond to a strategy to reduce losses by installing multiple shorter circuits rather than fewer longer circuits[18].

The expansion dynamics of these two types of systems are quite different. Aggregate capacity grows faster in the "traditional" scenario compared to the distributed scenario. For example, there is ~7.5 GW of distribution capacity in the dense area in both scenarios by 2020. This capacity grows to 15 GW in the distributed scenario and 22 GW in the traditional scenario by 2030. This reflects that in a traditional system the distribution grid grows with peak demand, but with DER peak demand is met at the node level. Aggregate circuit length is relatively similar across scenarios, but grows much faster in low density than in high density areas for both cases. As we show later, this reflects the optimal electrification sequencing in low density areas wherein nodes closer to the feeder header are connected first. This also reflects that in dense areas the optimal grid extension does not change in time and the 2020 grid length is very similar to the 2030 grid length.

B. The SWITCH model

SWITCH is a deterministic linear programming algorithm that concurrently optimizes investment and operation of generation and transmission while meeting a detailed set of operational and policy constraints. Unlike many capacity expansion models for the electricity sector, SWITCH incorporates high spatial and temporal resolution for each region analyzed. In general terms, the model represents the transmission network by aggregating portions of transmission infrastructure that do not present persistent congestion. Each one of these portions is called a "load zone". Generation (centralized and distributed) and consumers are grouped in these load areas consistent with the topology of the simplified transmission system. For temporal representation GAP uses sample hours to match capacity and demand in each one of these hours, weighting the latter to represent energy needs for the whole horizon. Temporal synergies between demand and variable non-dispatchable supply are systemically captured through this novel approach.

The objective function for SWITCH is to minimize total system costs, as indicated analytically in equation (S1).

$$System\ Cost = \min\left\{\sum_{p,u}\rho_{\rho}\cdot\left(k_u\cdot I_{p,u}^{G,T}+F_{p,u}^{G,T}\right)+\sum_{h,u}\rho_{p(h)}\cdot\left(C_{h,u}^{F}+C_{h,u}^{M}+C_{h,u}^{C}\right)\cdot D_{h,u}^{G}\cdot w_h+\sum_{p,r}\left(k\cdot I_{p,r}^{D}+C_{p,r}^{M}\right)\right\} \tag{S1}$$

[18] This specific behavior may also be explained by the absence of fixed costs in circuit deployment. GAP parameters and variables are linearized to avoid solving a computationally intensive MILP problem.

where $I^{G,T}_{p,u}$ are investment in generation G and transmission T in period p and for unit u; $F^{G,T}_{p,u}$ are their respective fixed costs; $C^{F}_{h,u}$ is fuel cost per operating hour h per unit u, $C^{M}_{h,u}$ are O&M costs, and $C^{C}_{h,u}$ are carbon costs, all multiplied by hourly dispatch $D^{G}_{h,u}$ and weighted by factor w_h; $I^{D}_{p,r}$ is investment in distribution in period p and load area r and $C^{M}_{p,r}$ its respective O&M costs. For efficient notation, a generation unit u is defined as a specific technology in a given location and a transmission unit u is an interconnection between two load areas. Investment costs are annualized through a capital recovery factor k_u and all costs are discounted to present using ρ_p.

C. Random graph generation algorithm

This list describes the process for the random graph generation to create and spatially situate nodes and distribution links:

1. We create a shapefile with polygons that represent each load zone. In this implementation, we use Kenya's administrative divisions as a base to create load zone polygons.
2. Create n nodes on each polygon using the *spsample* function of the *sp* package in R. This function creates randomly located latitude and longitude for each node within a given polygon.
3. Produce k pairs of nodes that are joined through a distribution link, akin to an edge. The likelihood or probability of a pair of nodes to be joined is inversely proportional to their distance. We use a normal distribution to map distance to likelihood of interconnection.
4. Run a routine to make sure all nodes are connected to at least another node. If a node is found to be unconnected, a distribution link to the closest neighbor is created. This is to ensure the graph is connected to prevent mistaken off-grid solutions for nodes that do not have any distribution path to them.
5. During the calibration, we ran a routine that checked the maximum and median number of links per node. We adjust the likelihood of linking to match a median of 5 to 6 links per node.

D. Additional tables

Table B.1 Investment, fixed, and variable non-fuel costs by technology.

Technology	Fixed cost kW-yr	Variable non-fuel cost $/MWh	Investment cost Th$/MW (except battery energy storage, in $/kWh)			
			2020	2025	2030	2035
Battery Storage (capacity $/MW)	28	0.6	612	576	514	460
Battery Storage (energy $/kWh)	NA	NA	306	240	206	192
Bio Gas Internal Combustion Engine	124	0.0	2,579	2,579	2,579	2,579
CCGT (Combined Cycle Gas Turbine)	7.2	2.7	840	822	804	787
Coal Steam Turbine	29	4.2	3,246	3,246	3,246	3,246
DistillateFuelOil Combustion Turbine	18	4.2	489	489	489	489
DistillateFuelOil Internal Combustion Engine	18	4.2	489	489	489	489
Gas Combustion Turbine	16	3.7	556	556	556	556
Geothermal	48	3.4	1,964	1,893	1,825	1,759
Reservoir hydropower	13	0.0	1,959	1,959	1,959	1,959
Run-of-river hydropower	6.7	0.0	1,959	1,959	1,959	1,959
Solar PV	50	0.0	937	841	772	718
Wind	14	5.1	1,668	1,550	1,440	1,338

Table B.2 Numerical values for generation and transmission operational parameters.

Constraint	Value	Unit	Notes
Planning reserve margin	15%	of annual peak load	Additional capacity required for resource adequacy
Load only spinning reserve requirement	3%	of load	Traditional spinning reserve requirement for load following only
Wind-specific spinning reserve requirement	5%	of installed wind capacity	Additional spinning reserve proportional to wind deployment
Solar-specific spinning reserve requirement	5%	of installed solar PV capacity	Additional spinning reserve proportional to solar PV deployment
Spinning reserve ramping constraints: CCGT	25%	of installed capacity	Maximum available capacity to provide spinning reserve on a given unit. Corresponds to the 10-minute ramp rate

Constraint	Value	Unit	Notes
Spinning reserve ramping constraints: SCCT and engines	30%	of installed capacity	Maximum available capacity to provide spinning reserve on a given unit. Corresponds to the 10-minute ramp rate
Minimum storage requirement for spinning reserve	1	hour	Minimum hours of storage that need to be available for a given storage unit to provide spinning reserve
Heat rate spinning reserve penalty: CCGT	30%	of nominal heat rate	Additional heat rate penalty incurred by units of this type of technology when providing spinning reserve.
Heat rate spinning reserve penalty: SCCT ane engines	9%	of nominal heat rate	Additional heat rate penalty incurred by units of this type of technology when providing spinning reserve.
Quickstart reserve	3%	of load	Additional capacity required as operation reserve
Ramp up costs: CCGT	9.16	MMBTu/MW	Additional fuel cost for ramping a CCGT
Ramp up costs: SCCT and engines	0.22	MMBTu/MW	Additional fuel cost for ramping a gas or diesel turbine/engine
Minimum loading for baseload	100%	of installed capacity	Applies to geothermal, CCS, cogeneration, and nuclear plants (if they exist)
Minimum loading for flexible baseload	40%	of installed capacity	Applies to coal steam turbines
Minimum flow for reservoir hydropower	50%	of available reservoir hydro capacity	Minimum dispatch requirement for reservoir hydro to mimic minimum downstream flow requirements
Hydropower operating reserve limit	20%	of available reservoir hydro capacity	Limits to 20% how much hydropower capacity is available to be used as spinning reserve.
Storage discharge rate	100%	of installed capacity	How much of the installed capacity can be discharged on a given hour. Set at the same value as the installed capacity
Storage roundtrip efficiency	77%	of stored energy	Percentage of energy that is not available after being stored.

E. Additional result figures

Figure B.1 Aggregate hourly dispatch for utility scale and distributed diesel generation for least cost scenario with no distributed PV or storage.

Figure B.2 Aggregate hourly dispatch for utility scale and distributed diesel generation for least cost scenario with distributed PV or storage.

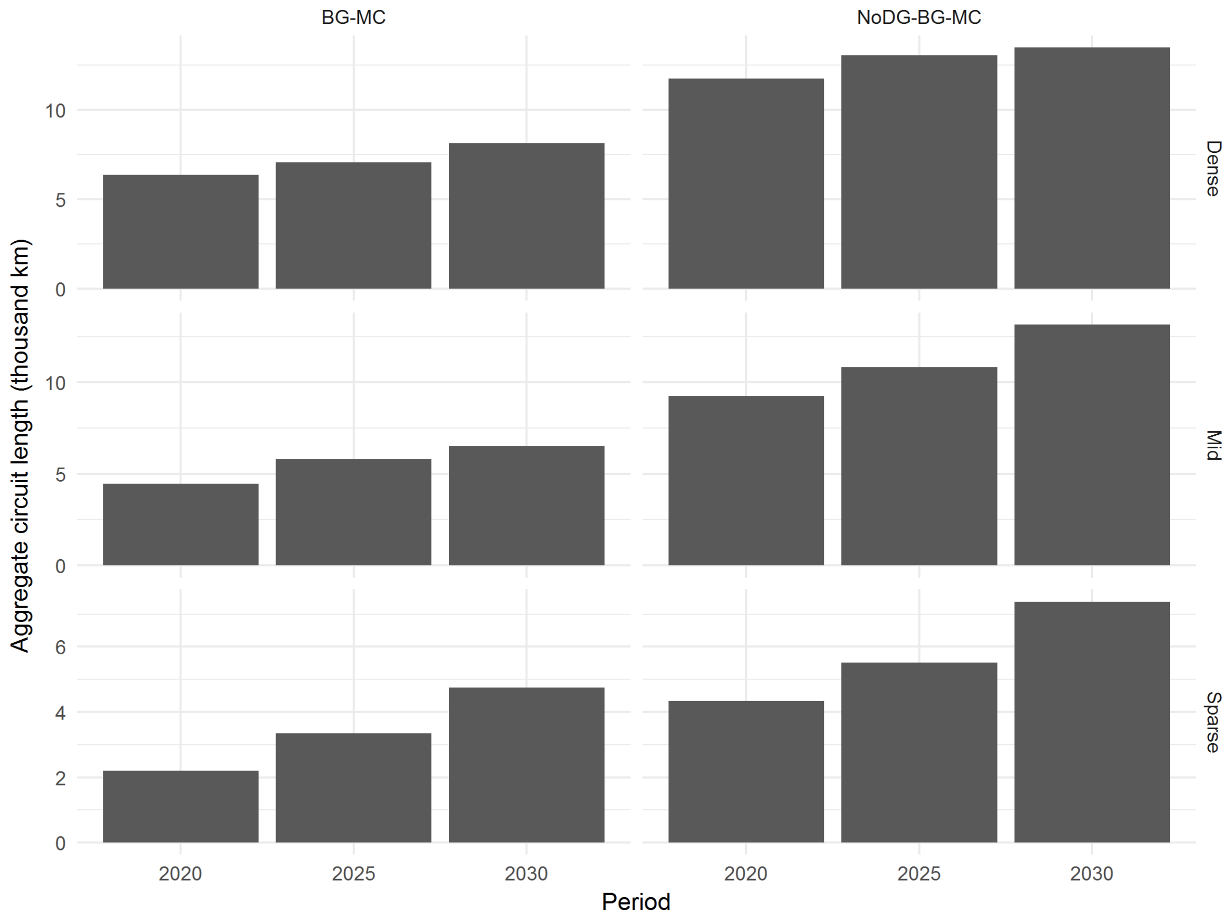

Figure B.3 Aggregate circuit length by period and density category for the "traditional" (NoDG) and distributed resource scenarios

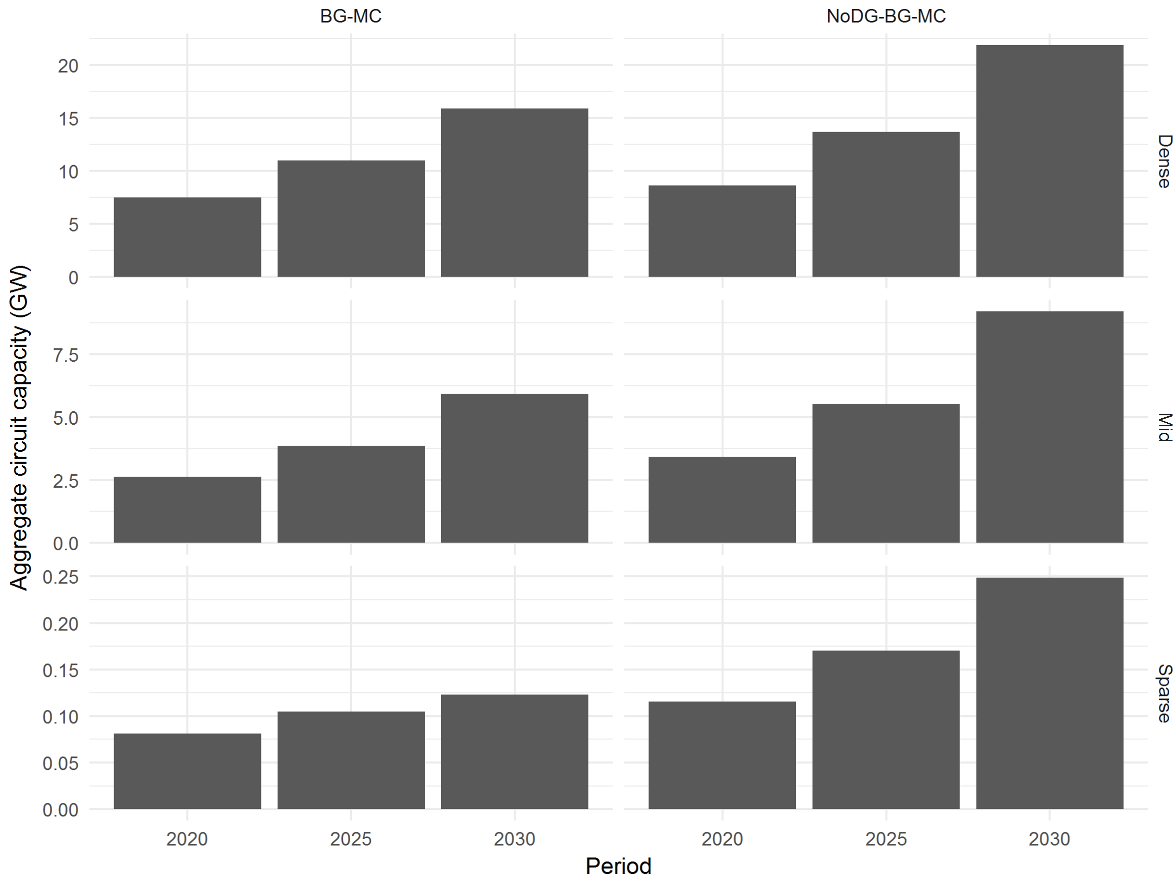

Figure B.4 Aggregate distribution circuit capacity by period and density category for the "traditional" (NoDG) and distributed resource scenarios

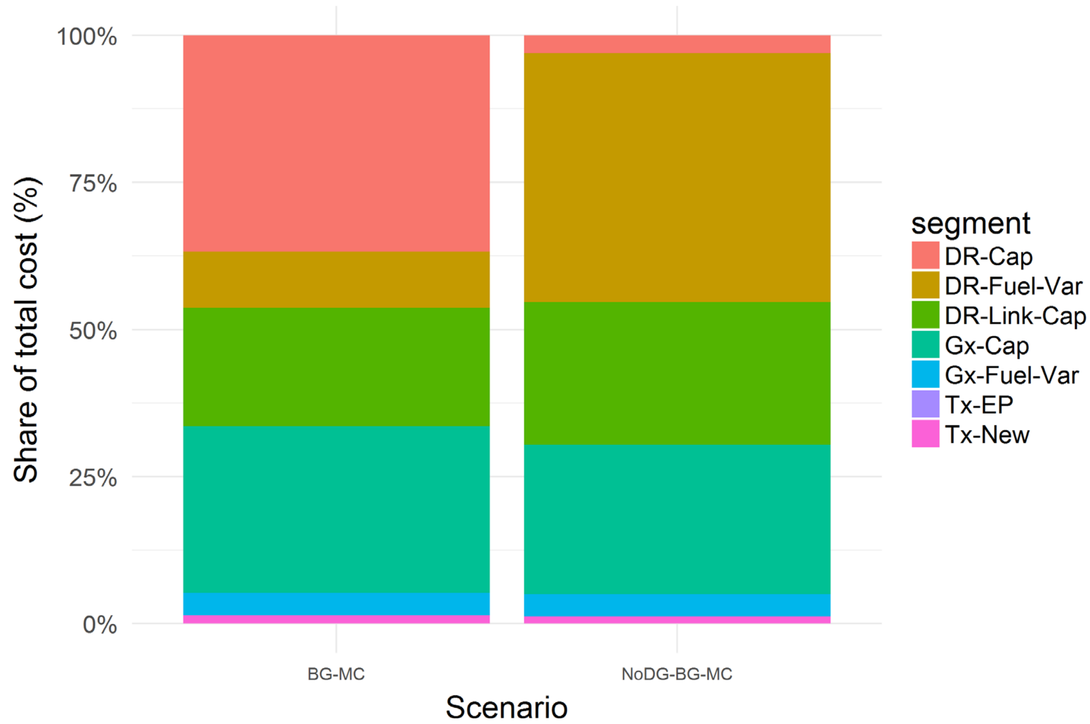

Figure B.5 Share of total system costs for the "traditional" and distributed resource scenarios.

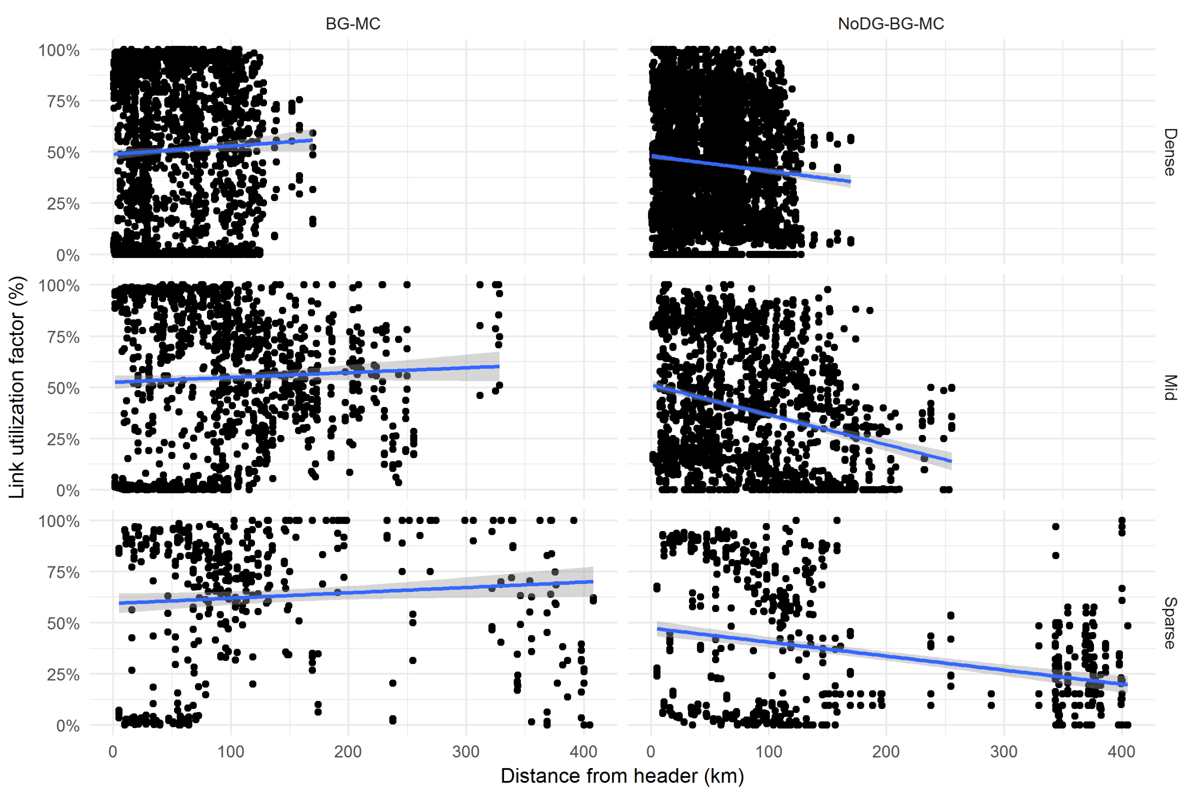

Figure B.6 Link utilization factor as a function of distance from link to feeder header for the traditional expansion and distributed resource expansion scenarios.

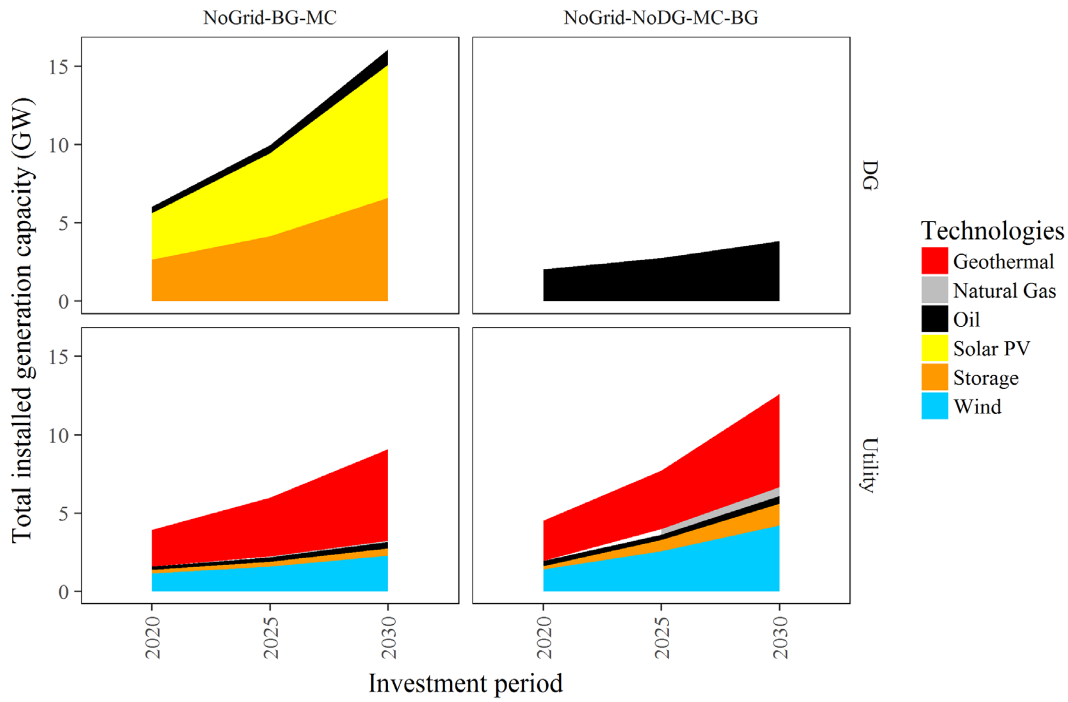

Figure B.7 Installed generation capacity by period for the traditional and distributed resource expansion scenarios.

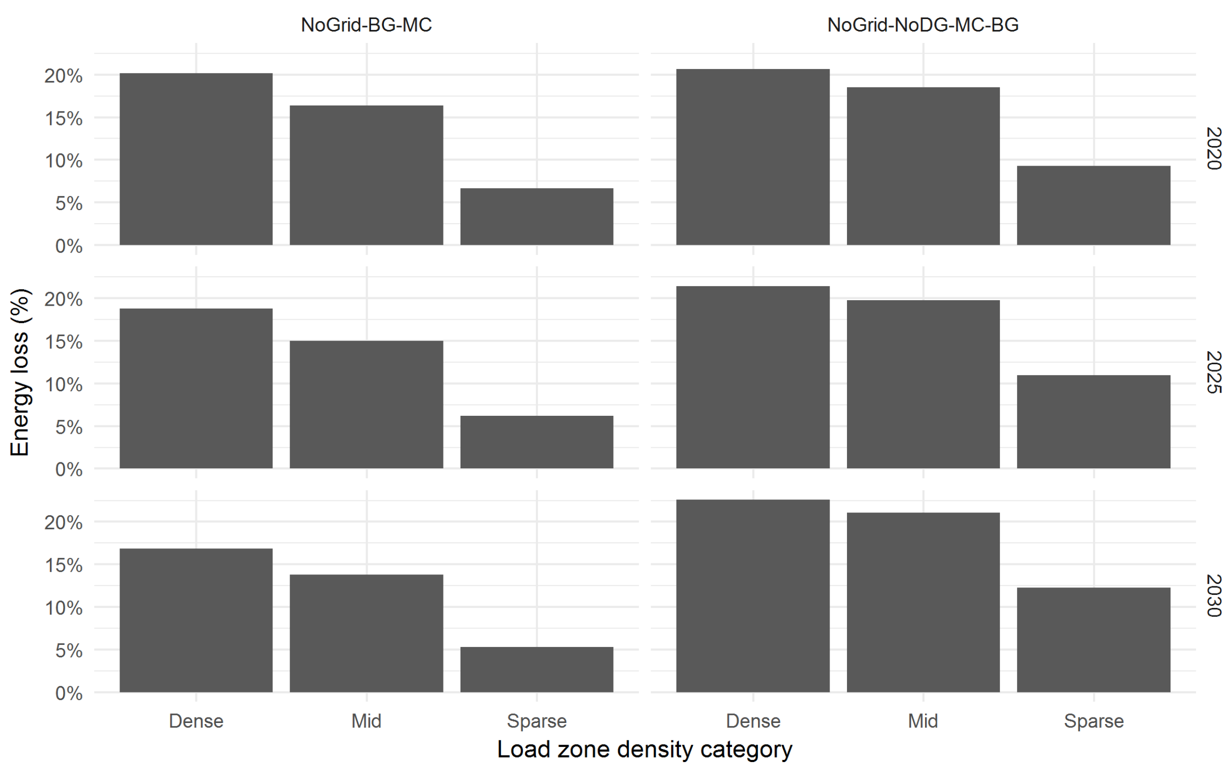

Figure B.8 Energy losses by period and load zone density category for the "traditional" and distributed resource scenarios.

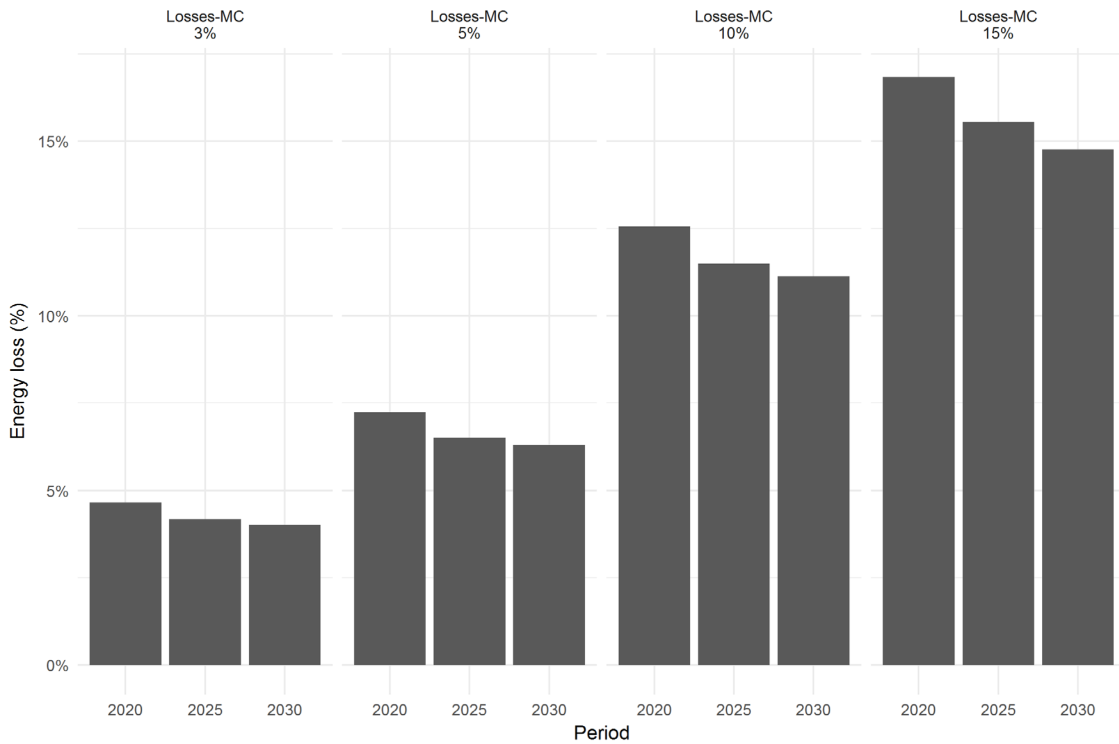

Figure B.9 Energy losses as a function of the GAP model efficiency parameter.

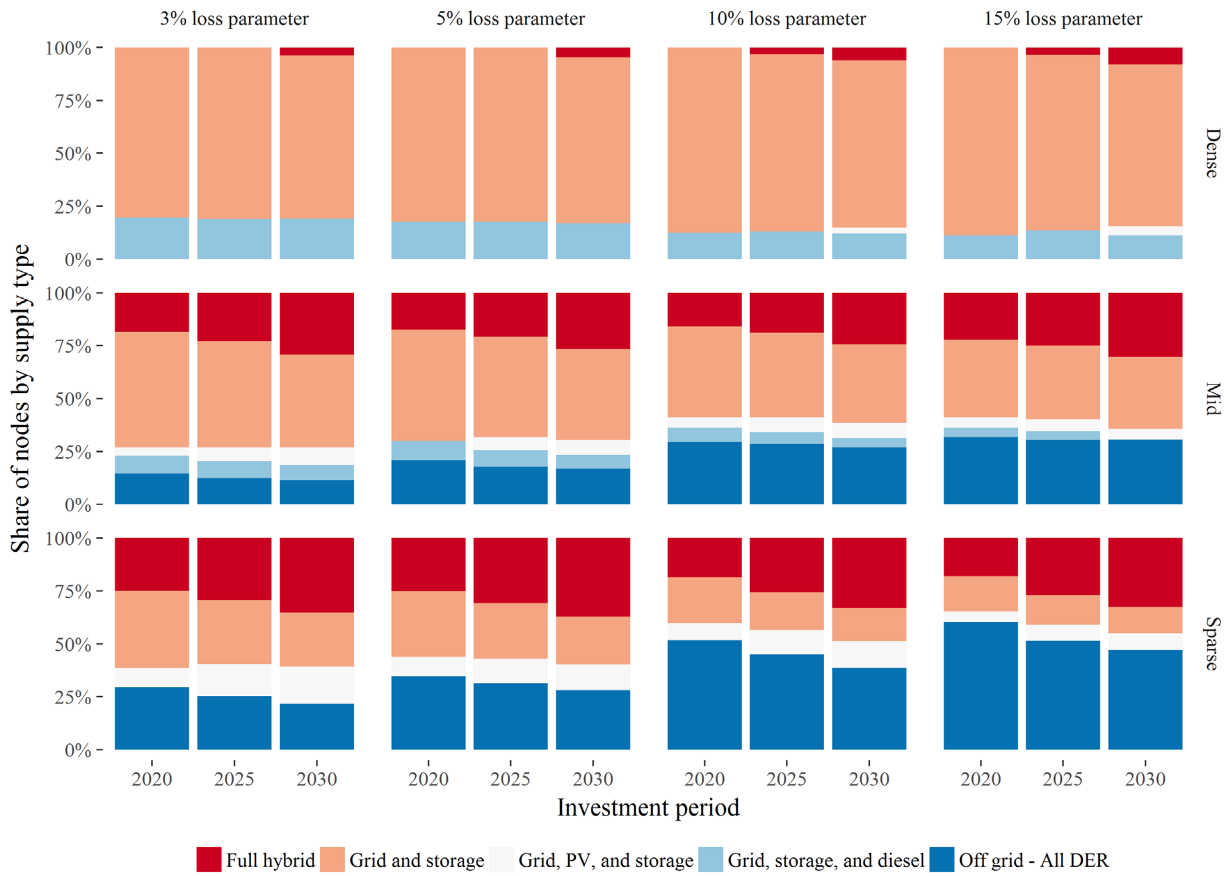

Figure B.10 Supply mode for different GAP model distribution efficiency parameters.

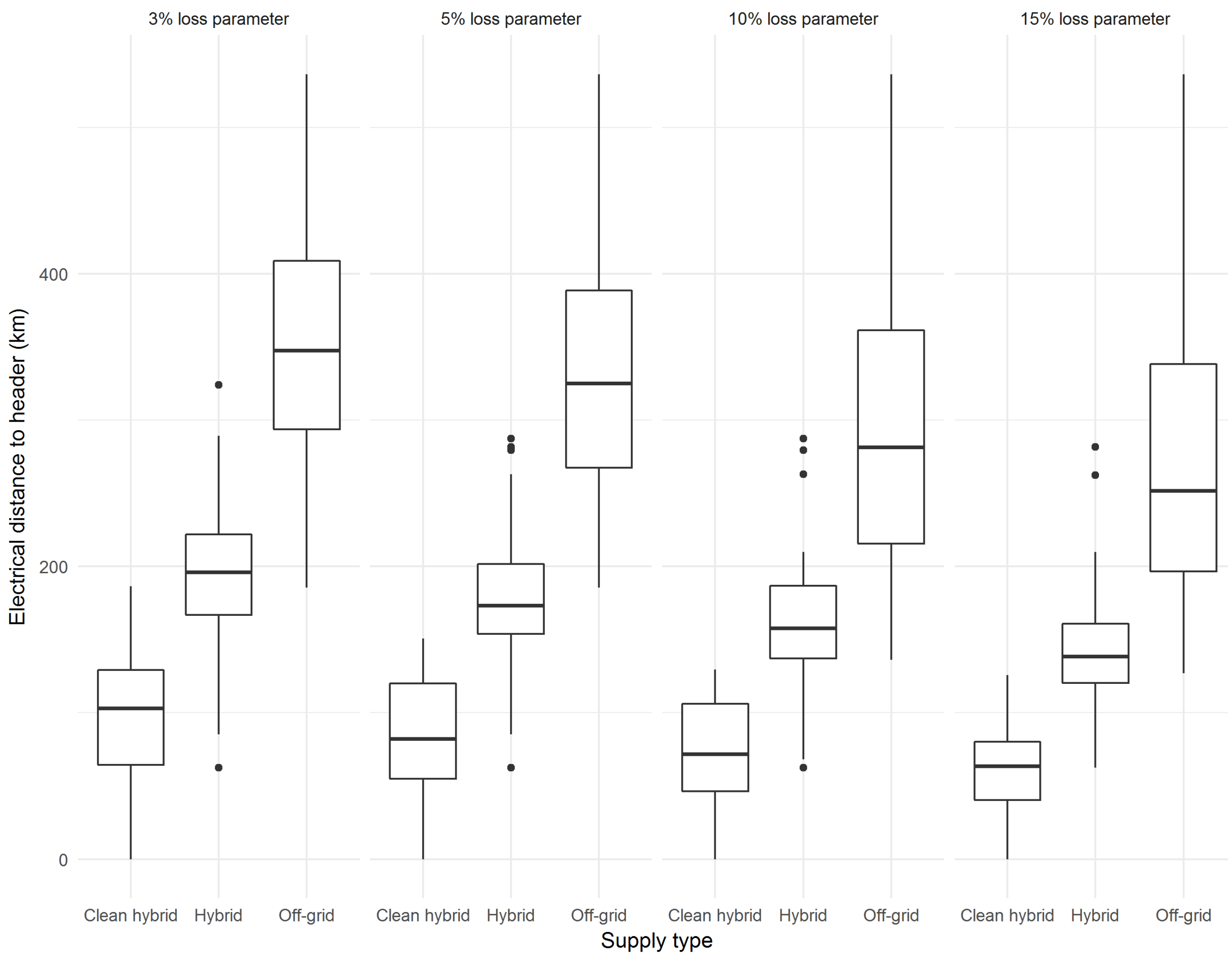

Figure B.11 Sparse area supply mode as a function of distance for different GAP model distribution efficiency parameters.

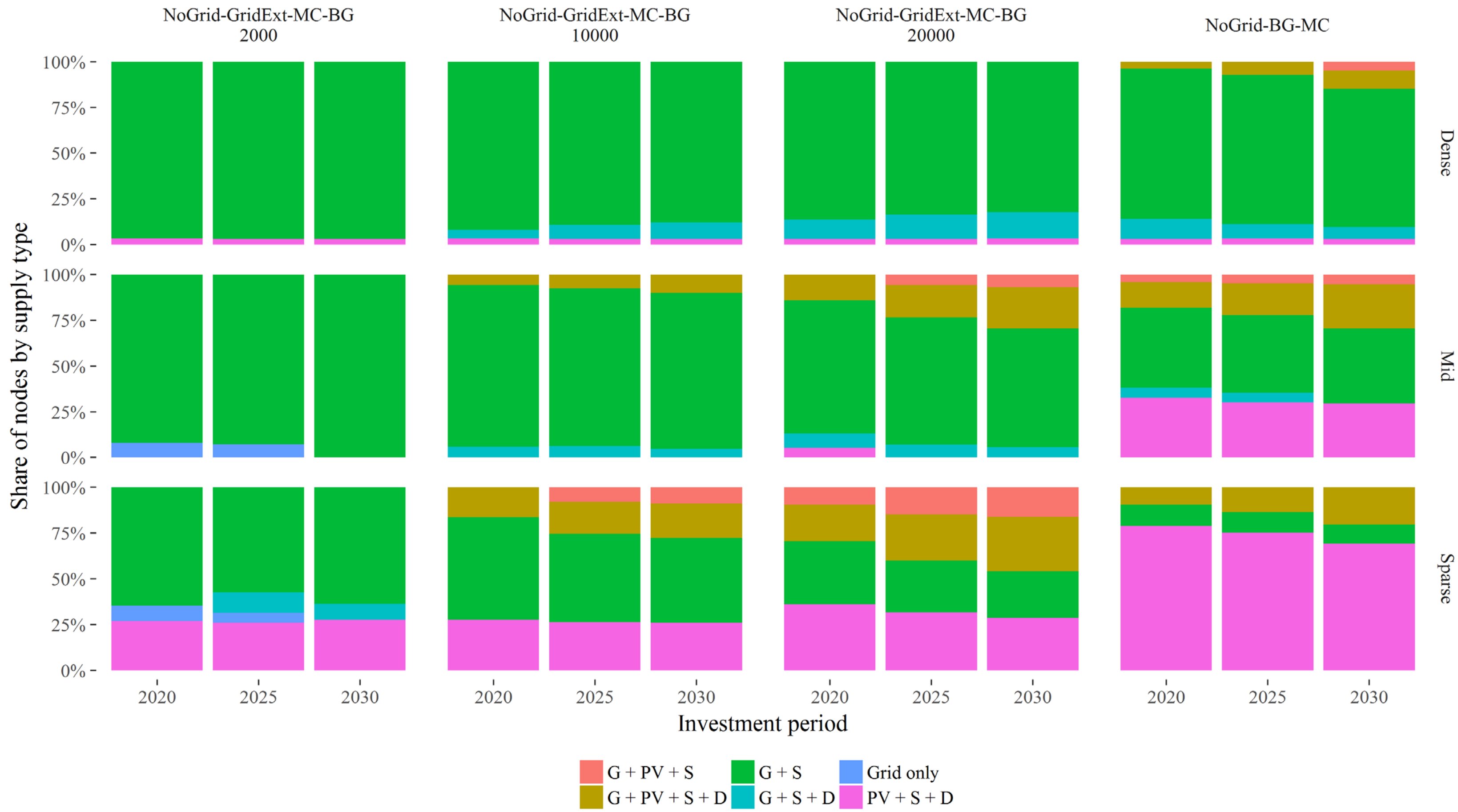

Figure B.12 Supply mode under three grid extension cost sensitivity scenarios

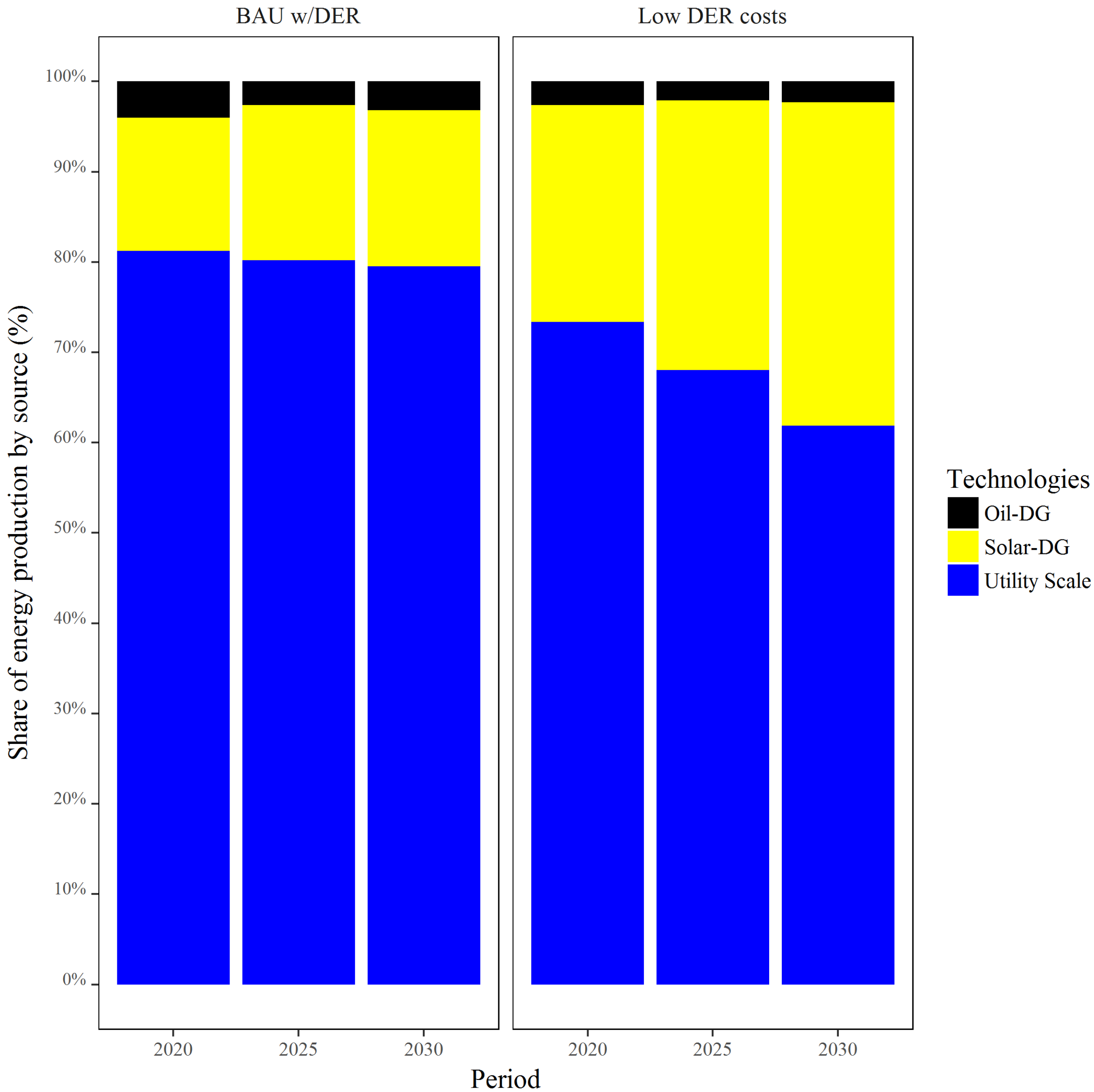

Figure B.13 National level energy balance by period and technology for the distributed scenario and a low PV and storage capital cost sensitivity scenario.

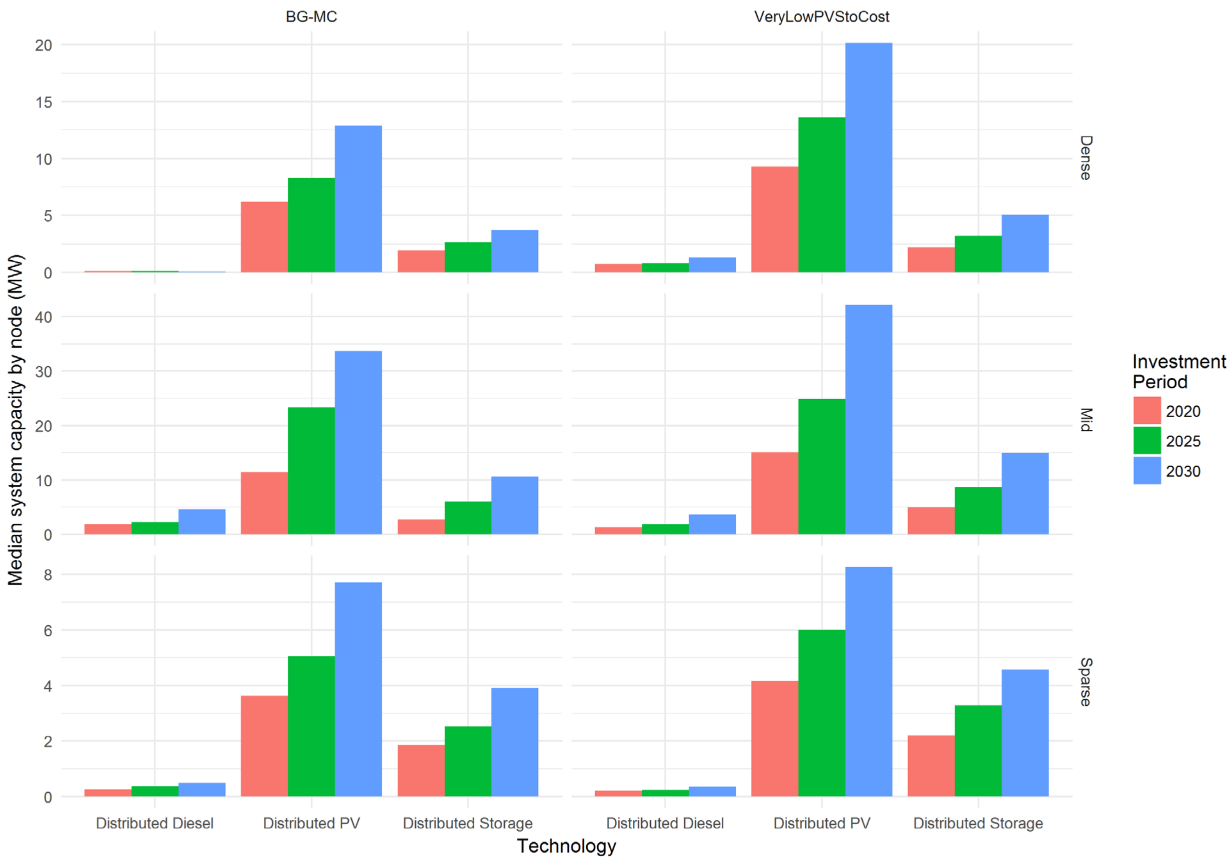

Figure B.14 Median system capacity by node, technology, and load zone density category.

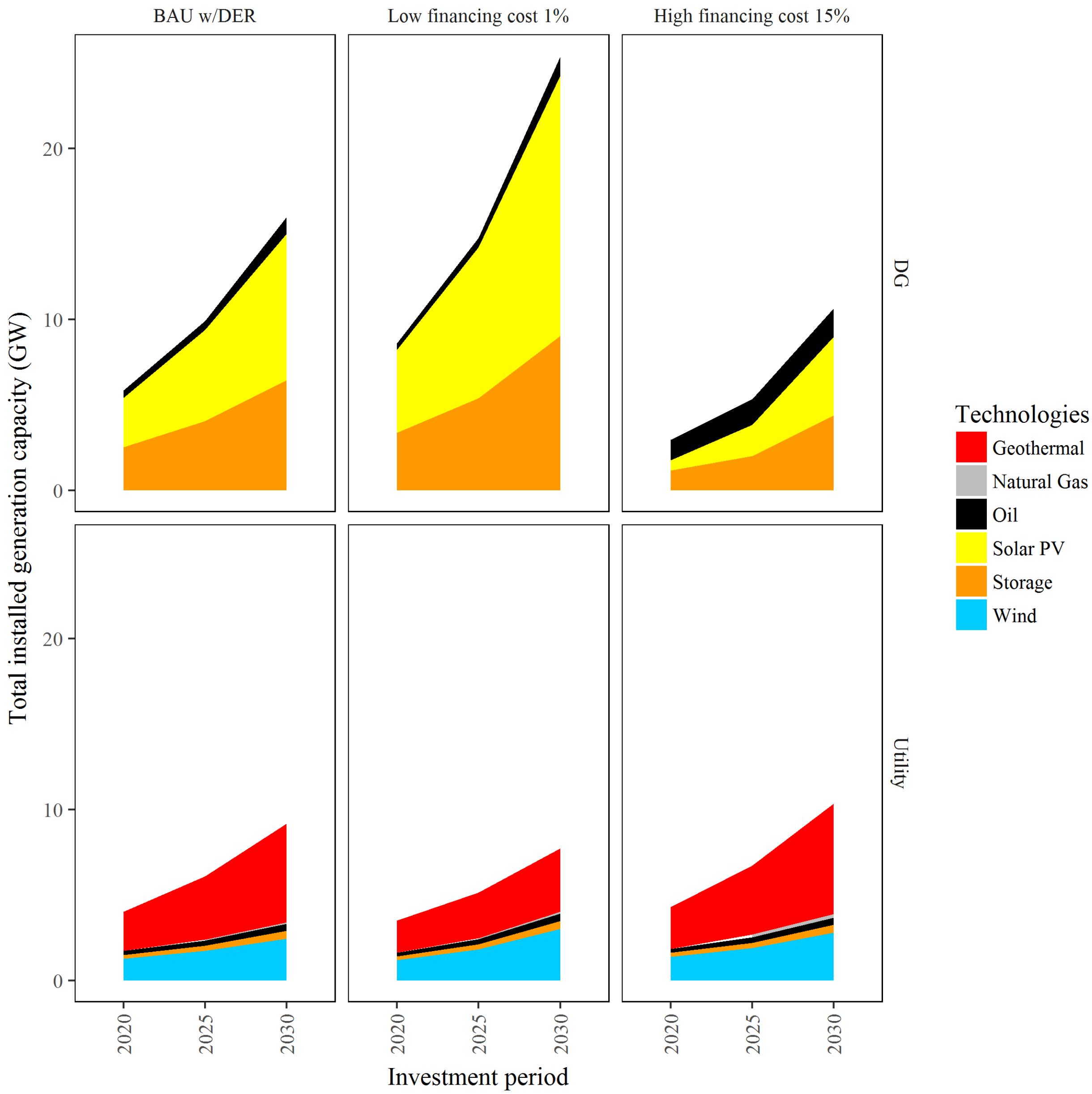

Figure B.15 System capacity for the high and low financing rate scenarios, compared to the base scenario.

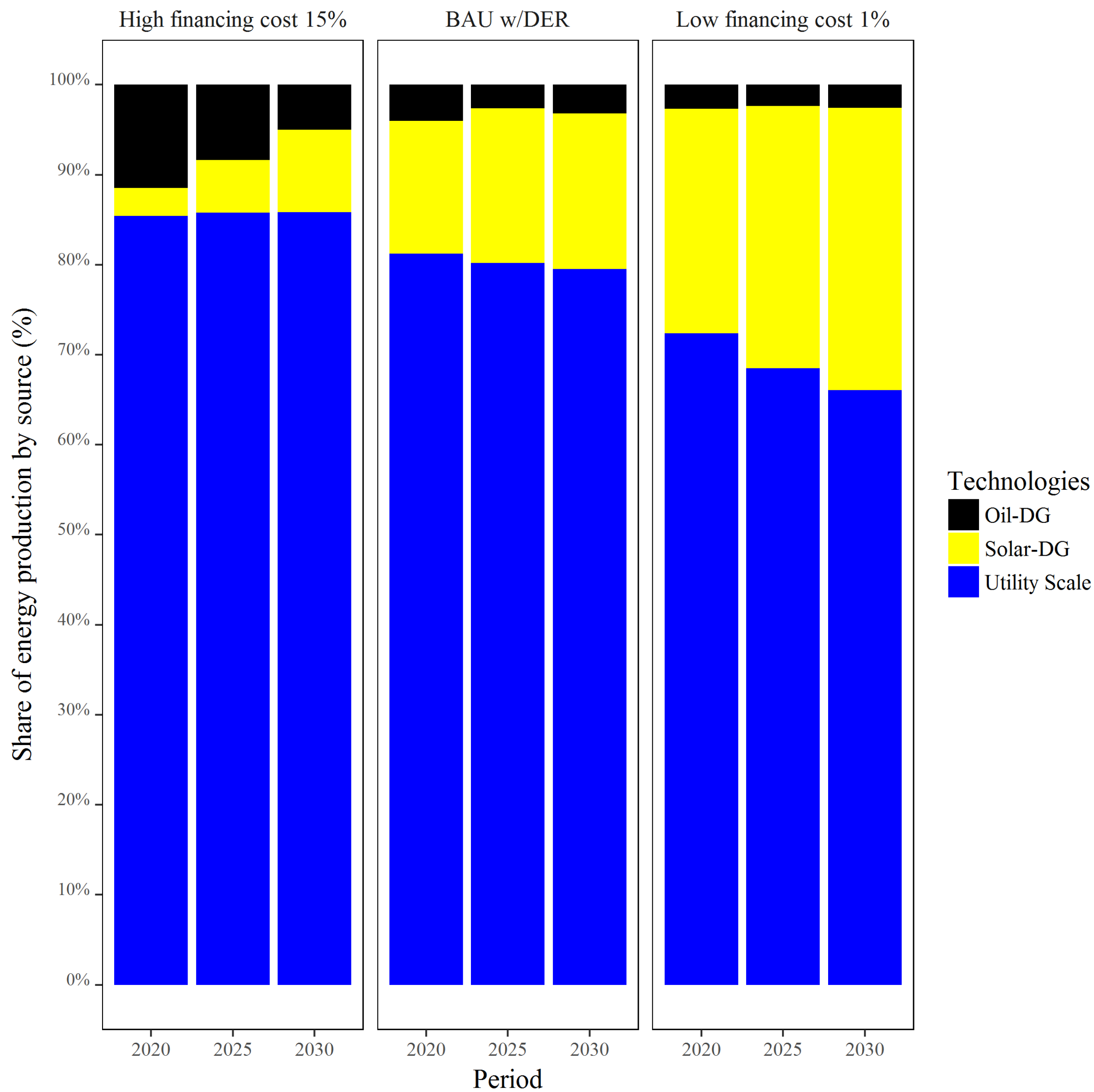

Figure B.16 Share of energy supply by source for the high and low financing rate scenarios, compared to the base case.

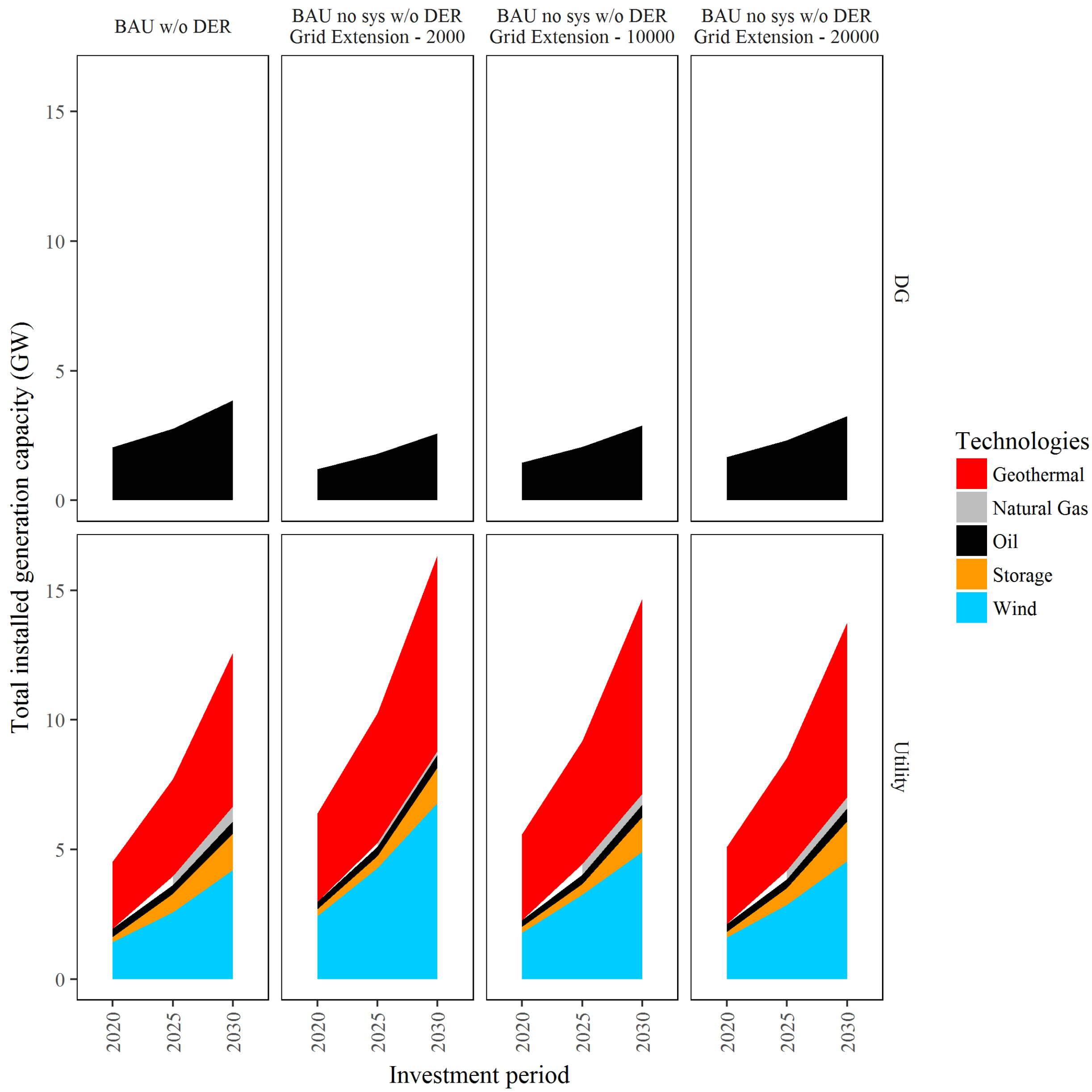

Figure B.17 System capacity for the grid extension sensitivity scenario compared to the base scenario, both without including DER.

Appendix C

A. Additional results figures

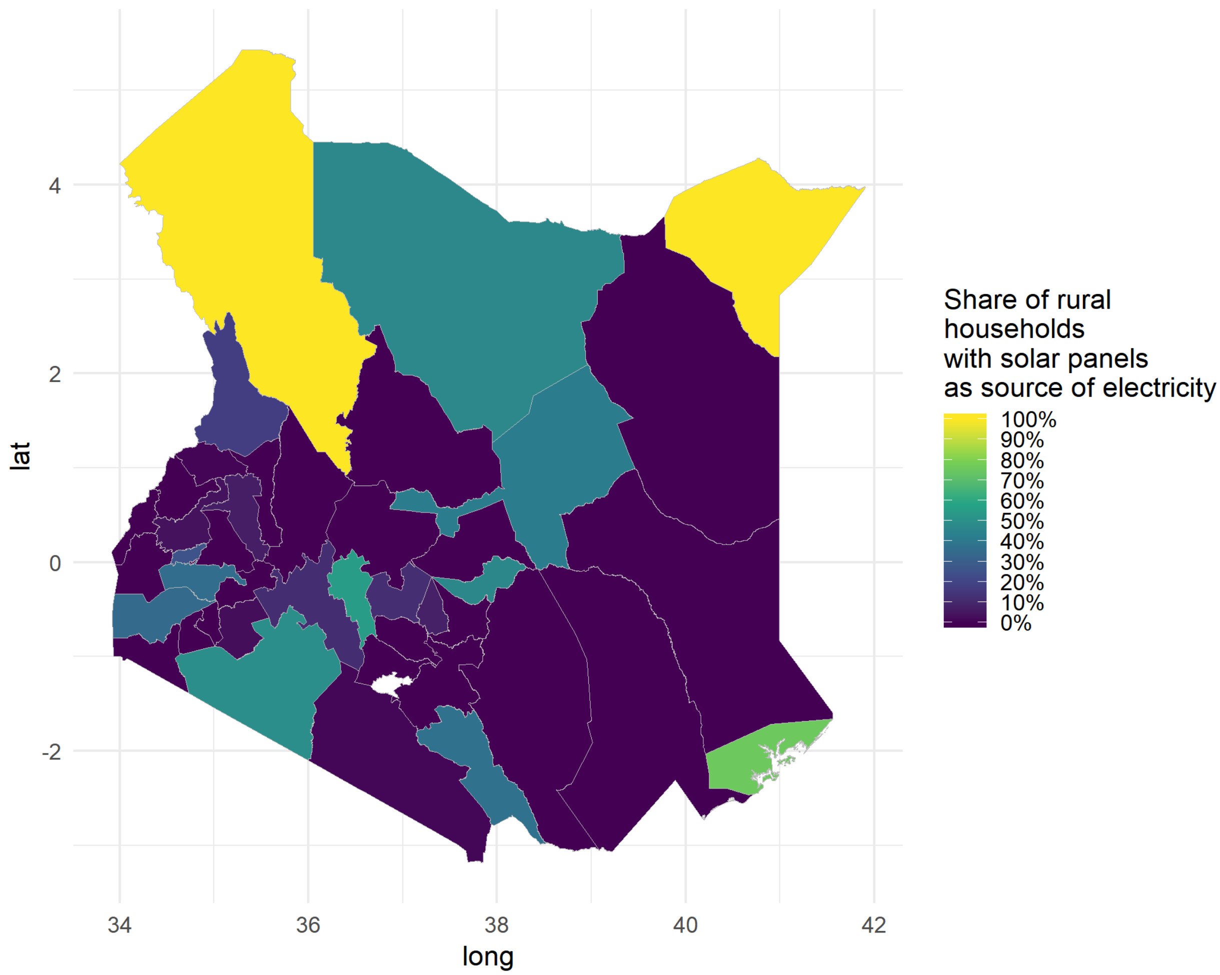

Figure C.1 Share of households reporting solar panels as their main source of electricity

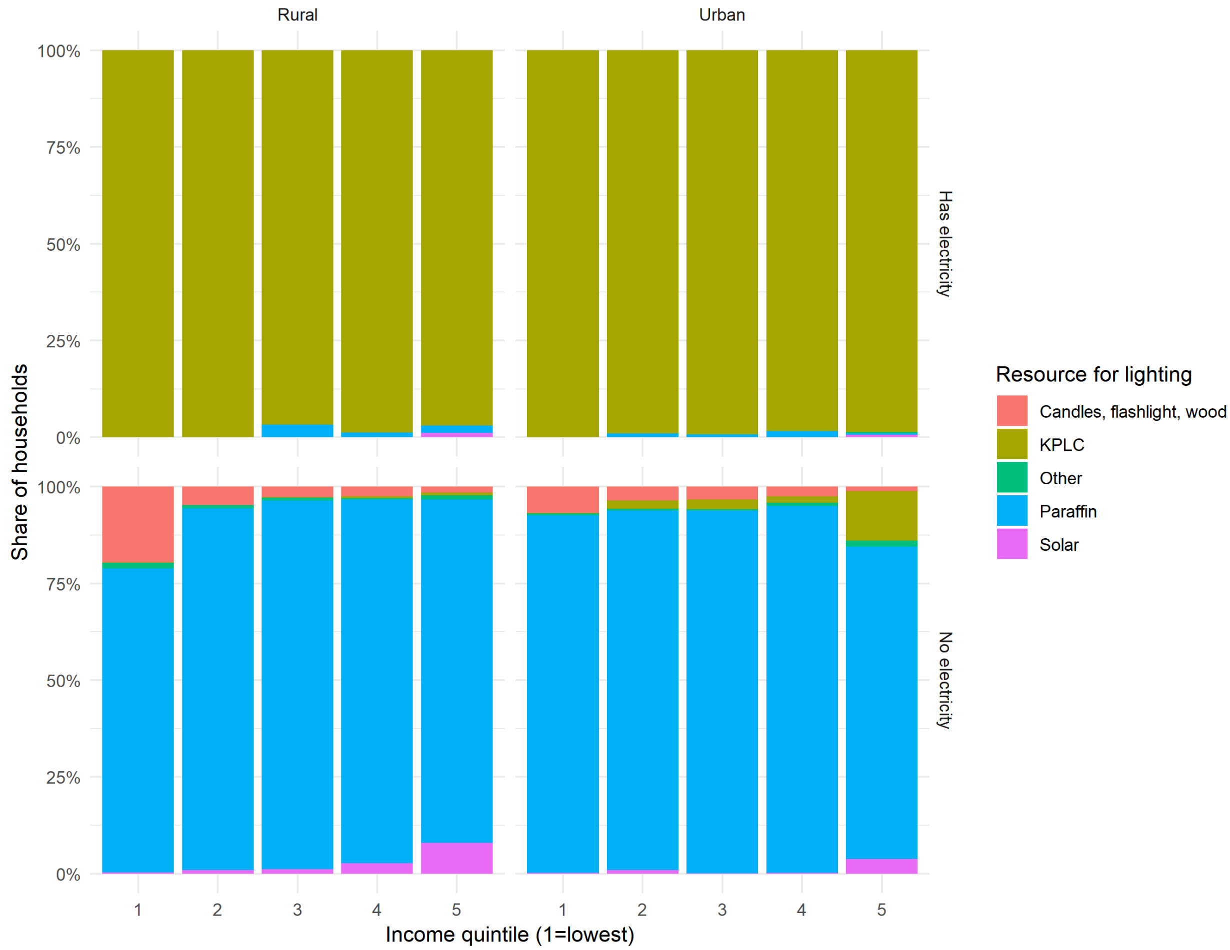

Figure C.2 Share of households using a primary lighting source by income, rurality, and access to electricity for the 2006 KHBS

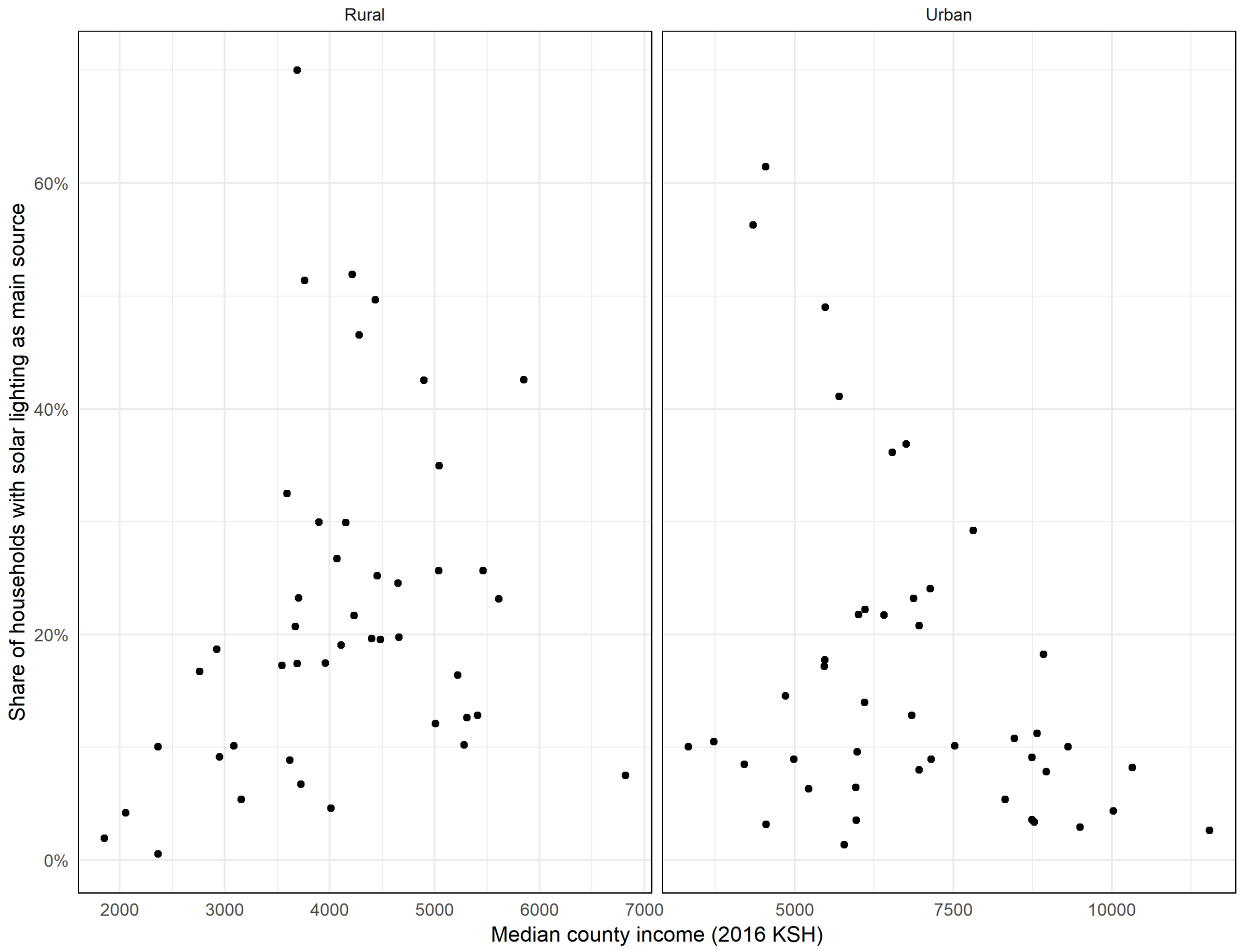

Figure C.3 Share of unconnected households by county that declare solar lighting as their main source, by median county income

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